AN EVALUATION OF CROSS-YEAR CROP CLASSIFICATION FOR THE STATE OF KANSAS USING TIME-SERIES MODIS 250m VEGETATION INDEX DATA

By

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of

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ABSTRACT

In many cases, when classifying satellite imagery, training sites and sample data are not available on a yearly basis. Many locations might only have complete, quality ground data for a single year over a period of a decade or more. Therefore, it would be beneficial if accurate training data from a single year could be applied to other years.

The objectives of this research were to: 1) utilize time-series MODIS 250m NDVI data to identify and map unique crop types for the state of Kansas and the surrounding Kansas River watershed and 2) test the level of accuracy when conducting cross-year classifications by applying a library of NDVI time-series curves to imagery from other years.

MODIS 250m NDVI data were used to classify seven unique crop cover types for 2005, including winter wheat, corn, soybeans, sorghum, alfalfa, fallow, and double crop. The classified maps' patterns were consistent with the cropping practices of the study area and an overall accuracy of 82% was achieved.

MODIS 250m time-series NDVI data along with Common Land Unit (CLU) and Farm Service Agency (FSA) training and validation data from 2001 and 2005 were used to conduct the cross-year classifications. Overall accuracies were found to be between 68% (2001) and 74% (2005). The general patterns of the classified maps were consistent with the state's cropping practices. The relatively low accuracy levels are likely due to variations in climatic events and farming practices between the two years.

ACKNOWLEDGEMENTS

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INTRODUCTION

1.1 CONTEXT AND STATEMENT OF PROBLEM

Agricultural landuse/landcover data are among the most important and universally used terrestrial spatial data sets (IGBP, 1990). Up-to-date maps and data sets that map specific crop types are needed over intensively cropped regions for applications focused on understanding the role and response of the agricultural sector to environmental change issues (Wardlow et al, 2007). The cropland component of the agricultural landscape is of specific interest because it is intensively managed and has dynamic land cover patterns. Cropland patterns are continually modified by a wide range of human activities like crop rotations and fallowing as well as the introduction of new crops or discontinuation of former crops. As a result, detailed regional-scale cropping patterns need to be mapped on a repetitive basis in order to characterize dynamic land use/land cover patterns and monitor common changes (Wardlow, et al 2007).

Landuse/landcover datasets, however, are only useful if they are sufficiently accurate for the required application. Traditionally, in situ training or sample data from a given year are used for classifying satellite imagery for the same year. Unfortunately, in many cases training sites and sample data are not available on a yearly basis. Many locations might only have complete, quality ground data for a single year over a period of a decade or more. Therefore, it would be beneficial if accurate training data from a single year could be applied to other years. The focus of this study is to help determine if a “library” of standard NDVI time-series curves can be used to classify crop types: in simple terms, to examine if one good training dataset can be applied to classify multiple years. For this study the focus will be on using training samples of 2001 cropland data to classify 2005 cropland data and vice versa for the state of Kansas. The goal will be to determine whether classification accuracies for these cross-year classifications will be comparable to those achieved when using training data from the same year as the satellite imagery.

1.2 RESEARCH OBJECTIVES/QUESTIONS

For this study I worked with two years’ of Moderate Resolution Imaging Spectroradiometer (MODIS) Normalized Difference Vegetation Index (NDVI)-derived crop training samples for the state of Kansas. I used Brian Wardlow’s 2001 (Wardlow, 2005) classified datasets and Iwake Masialeti’s 2005 (Masialeti, 2008) datasets. There are several objectives I sought to address in this research.

General objectives

1) What level of classification accuracy will be achieved for 2005 when using training data from the 2005 USDA Common Land Unit (CLU) dataset? How does this 2005 CLU based classification compare to Wardlow’s 2001 classification that used training data derived from FSA crop photo data, i.e. can his results be replicated with a different year?

2) Can training data from 2001 be used to classify the 2005 data at an acceptable level of accuracy?

3) Can training data from 2005 then be used to classify the 2001 data at an acceptable level of accuracy?

Specific objectives

1) Can Wardlow's results for 2001 be replicated for 2005?

2) What level of classification accuracies can be achieved using cross-year training data?

3) How do these accuracies vary spatially and by crop type?

4) How do the cross-year classification accuracies (2005<>2001) compare to the same-year based classification accuracies (2005<>2005 and 2001<>2001).

5) Do the accuracies suggest that this cross-year classification method could be extended spatially and temporally?

1.3 LITERATURE REVIEW

Landcover Mapping

For over 20 years time-series data from wide-field sensors has been used for landuse/landcover mapping. Initial Advanced Very High Resolution Radiometer (AVHRR) derived land cover classifications were produced for Africa (Tucker *et al.*, 1985) and South America (Townshend *et al.*, 1987) using multi-temporal NDVI data.

DeFries and Townshend (1994) generated an 11-class, 1-degree resolution global land cover map from monthly composited NDVI data in support of climate modeling. DeFries *et al.* (1998) improved upon this effort by creating a 13-class global land cover map from the same data set. Loveland *et al.* (1991) derived the first complete land cover map for the conterminous U.S. using 1-km multi-temporal AVHRR NDVI data. In Loveland et al.'s work, seasonal land cover regions (i.e., those that exhibit unique phenological characteristics and represent relatively homogeneous vegetation associations) were classified from a time series of monthly composited NDVI data and other ancillary data sources (e.g., climate and terrain variables). Loveland *et al.* (1999) applied this classification concept globally to produce a similar 1-km global, multidimensional land cover database. Hansen *et al.* (2000) built upon the previous 8-km work of DeFries *et al.* (1998) and generated a global, 14-class general land cover map using a 12-month time-series of monthly composited 1-km AVHRR data. Currently an operational, global 1-km land cover product is being produced annually from multi-temporal, multi-spectral MODIS data (Friedl *et al.*, 2002). In recent years, the application of MODIS data for landuse/landcover mapping has become widespread (Wardlow and Egbert, 2007; Xiao et al., 2006; Xavier et al., 2006).

Decision Tree Classifiers

For the purpose of this study a decision tree (DT) classifier was used. Decision tree classifiers are programs that break down a complex decision-making process into a collection of simpler decisions, thus providing a solution which is often easier to interpret. Previous research has demonstrated that DTs provide an accurate and efficient methodology for large-area land cover classification using remotely sensed data (Hansen *et al.*, 1996; Friedl and Brodley, 1997; DeFries *et al.*, 1998; Hansen *et al.*, 2000). DT approaches have consistently produced higher classification accuracies than traditional supervised classifiers (e.g., maximum likelihood) using both AVHRR and Landsat TM data (Hansen *et al.*, 1996; Friedl and Brodley, 1997). They also offer several other advantages over traditional classifiers (Hansen *et al.*, 1996) that are favorable for large-area LULC classification. It is for these reasons that Wardlow (2005) used the See5 classifier to map Kansas croplands. Currently, See5 serves as the classification algorithm for the production of the USGS NLCD 2001 product (Homer *et al.*, 2004) and its predecessor, C4.5, as the primary algorithm for the MODIS global land cover product (Friedl *et al.*, 2002).

Mapping Kansas Croplands

As previously mentioned, the study area for this research is Kansas croplands. Brian Wardlow (Wardlow, 2005) and Iwake Masialeti (Masialeti, 2008), in particular, have used MODIS NDVI data to map croplands in the state of Kansas for individual years. For his dissertation research, Wardlow mapped croplands in Kansas for 2001 and published articles based on this research (Wardlow and Egbert 2007; Wardlow et al 2007). Wardlow classified his 2001 cropland data using training site data gathered from USDA Farm Service Agency (FSA) crop photographs. He concluded that croplands in the Great Plains could be accurately mapped using time series MODIS 250m vegetation index data. Masialeti built on Wardlow’s work by analyzing NDVI time-series curves for Kansas crops in 2005 for his dissertation research. To date, Masialeti's 2005 dataset has not been used to create a land cover map, but it does include Common Land Unit (CLU) based training data. Masialeti extracted the NDVI signatures to determine if it was feasible that one training dataset (2005) could be used to classify data from another year (2001). Based on his work Masialeti tentatively concluded that temporal offsets in phenological curves between the years may negatively affect classification accuracies (the offset most likely being the result of climatic variation).

1.4 DATA

MODIS

The datasets utilized for this study were derived from Moderate Resolution Imaging Spectroradiometer (MODIS) imagery. The guiding philosophy behind the MODIS design was to collect daily coverage of well-calibrated multi-spectral, multi-resolution imagery from which higher-level quality data sets could be generated to meet the needs of the global change research community. Designed for land, oceanic and atmospheric applications, MODIS adopted a multi-spectral approach by incorporating 36 spectral bands, which cover the visible through long-wave infrared regions. Seven bands were carefully selected to capture the key spectral features of terrestrial targets, and their bandwidths were narrowed to avoid atmospheric absorption regions, particularly for the near infrared band (Justice *et al.*, 1998).

MODIS has a radiometric resolution of 12-bits for improved sensitivity to subtle reflectance differences. MODIS also includes several atmosphere-related bands that measure cloud properties, aerosols, and water vapor, and which are used to rigorously correct for atmospheric constituents and enable accurate surface reflectance values to be calculated (Justice *et al.*, 1998). Spectrally, MODIS contains two 250-m (red and NIR), five 500-m (blue, green, and MIR), and twenty-nine 1-km bands. The 250-m bands allow for the detection of human-induced land cover changes, many of which were found to occur at or near this spatial scale (Townshend and Justice, 1988). With the 250-m imagery, most individual fields of the Central Great Plains are large enough to be represented by multiple pixels (usually a minimum of 5 pixels) (Figure 1.1). The high temporal resolution (16-day composite period) of the time-series data is also favorable for discriminating crop types based on their unique crop calendars (phenology). MODIS also includes a 250-m Normalized Difference Vegetation Index (NDVI) data set, derived from the two 250-m bands.

NDVI

The cropland datasets for this study were compiled using a time-series of NDVI data. NDVI is a transformation that capitalizes on the differential responses of the visible red (absorbed by chlorophyll pigments) and NIR (reflected by the spongy mesophyll structure of leaves) spectral regions to vegetation and takes the form: NDVI = (NIR – red) / (NIR + red) (Rouse *et al.*, 1974). NDVI is a dimensionless, radiometric measure of green vegetation amount/condition that has been related to several biophysical variables such as biomass, Fraction of Photosynthetically Active Radiation (FPAR), and Leaf Area Index (LAI) (Asrar *et al.*, 1989; Baret *et al.*, 1991). NDVI provides a normalized range of values (-1 to +1) that are directly comparable over both space and time. In order to obtain relatively cloud-free global images, daily observations are composited over a defined time interval (Strahler *et al.*, 1999). A monthly composite period is typically used for global applications, while more localized studies utilize a shorter temporal window (e.g., 10-day or bi-weekly). It is these NDVI composites that have become the standard input for landcover mapping past and present.

Training Data

The training data utilized in this study come from two sources. Wardlow's (2005) 2001 training data were derived from United States Department of Agriculture (USDA) Farm Service Agency (FSA) aerial photos. Wardlow used these crop photos to assemble a state-wide field site database of specific crop types. This database consists of 1,240 non-irrigated sites from 51 counties. Masialeti's (2008) 2005 training data were derived from USDA FSA Common Land Unit (CLU) data. Masialeti utilized the 2005 Kansas CLU data layer to compile a state-wide field site database of specific crop types. This database consists of 1,254 non-irrigated sites from 64 counties. In addition, I generated training data for fallow and double crop landcover classes from the CLU data layer. This brings the final number of field sites to 1442.

1.5 STUDY AREA

This study was conducted in the state of Kansas along with the expanse of the Kansas River basin in portions of Nebraska and Colorado (Figure 1.2).

Kansas

The Kansas landscape is dominated by a cropland/rangeland mosaic with 46.9% (10.0 million ha) of its total area intensively cropped (Wardlow, 2005). The state's major crop types include alfalfa (*Medicago sativa*), corn (*Zea mays*), sorghum (*Sorghum bicolor*), soybeans (*Glycine max*), and winter wheat (*Triticum aestivum*). The state's pronounced east-west precipitation gradient strongly influences the specific cropping patterns and associated management practices (Figure 1.3). On average, western Kansas receives 457-505 mm (18-20 inches) of precipitation per year while eastern Kansas receives 889-1016 mm (35-40 inches) per year (USDA, 2002).

In semi-arid western Kansas, extensive irrigation from groundwater sources (i.e., the Ogallala and Dakota aquifers) and dryland farming techniques (e.g., crop-fallow rotations and no-till farming) maintain high crop production levels despite the area's limited precipitation regime. Approximately 21% (0.9 million ha) of the area's cropland is irrigated and primarily supports alfalfa, corn, and soybeans (USDA, 2002). The remainder of western Kansas is non-irrigated due to inaccessibility of groundwater or financial considerations. Most non-irrigated areas are planted to dryland crops such as sorghum or winter wheat or remain fallow in some years to conserve soil moisture for crop production the next year. The increasing adoption of no-till farming (direct planting of a crop into the crop stubble/residue from the previous year) as a soil moisture conservation technique has resulted in higher yields from traditional dryland crops, increased the acreage of crops with higher water requirements (e.g., corn) in historically non-irrigated areas, and lessened the reliance on crop-fallow rotations (Wardlow, 2005). In eastern Kansas, adequate precipitation is generally received in most years to support high crop production levels without irrigation. Corn and soybeans are the dominant crops in the east, and fallow land use practices are rare. Irrigation is very limited in eastern Kansas and is primarily applied in lowland floodplain areas where groundwater is readily accessible.

On average, Kansas has led the nation in both winter wheat and sorghum area (26.0% and 43.7% of the nation's total, respectively) and production (23.6% and 41.3% of the nation's total, respectively) (NASS, 2004). The economic importance of the state's cropland sector is reflected by its $3.6 billion in crop production in 2004, which ranked sixth nationally (NASS, 2004).

The average parcel size, or "grain", of the landscape also changes from western to eastern Kansas. Western and central Kansas are characterized by a coarse-grained landscape comprised of very large individual fields and large contiguous areas of both cropland and grassland or shrubland areas (Wardlow, 2005). Field sizes commonly range from 65 to 245 ha (160 to 600 acres). In contrast, cropland areas in eastern Kansas are more fragmented and interspersed with other land cover types (e.g., deciduous forest and grassland). Individual fields are also smaller, with most fields being 65 ha (160 acres) or less.

Nebraska

Most of Nebraska south of the Platte River, 16,916 square miles (43,812 km^2), is part of the Kansas River basin (Colby et al., 1956). This region of Nebraska is characterized by a north-to-south decrease in elevation and increase in temperature as well as an east-to-west decrease in mean precipitation. Precipitation averages range from 360 mm (about 14 in) annually in the west, to more than 860 mm (34 in) in the east.

Most of south central Nebraska is composed of loess plains and is farmed intensely. Southwestern Nebraska lies in the High Plains which are characterized by a large expanse of high flat tableland. This area receives little rainfall but some farming is accomplished with the use of center-pivot irrigation. The growing season ranges from 130 days in the west to more than 170 days in the east. Farmland occupies 18.5 million hectares (45.6 million acres), of which 47 percent is cropland. Some 34 percent of the cropland (mostly used to grow corn) is irrigated. The agricultural landscape consists of a mosaic of relatively large fields, with an average farm size of 388 ha (980 acres) (USDA, 2007).

Colorado

In addition, 8,775 square miles (22,727 km^2) in northeast Colorado is part of the Kansas River basin (Colby et al., 1956). The Eastern Plains of northeast Colorado are part of the High Plains, which are the westernmost portion of the Great Plains region. This section is some 150 miles (240 km) wide and covers more than a third of the state. It consists mainly of level to rolling land that slopes gradually upward from east to west to the foot of the Rocky Mountains. Elevations vary from about 3,400 feet (1,040 m) along the state's eastern border to as much as 6,000 feet (1,830 m) at the edge of the Rockies. The Eastern Plains have a semi-arid climate, like all of the High Plains, but receive lower rainfall than areas to the south and east. Rainfall is meager, averaging about 15 inches (380 mm) annually. The growing season ranges from 120 to 200 days on the High Plains. Farmland occupies 12.7 million hectares (31.3 million acres), of which 36 percent is used to grow crops. Winter wheat is the dominant crop and corn is the second most important crop grown in Colorado. There is some irrigated farming, but much of the land is used for dryland farming. Because annual rainfall fluctuates, the greater part of the plains is often too dry for cultivation every year. Therefore fallowing land and other forms of soil and water conservation are important.

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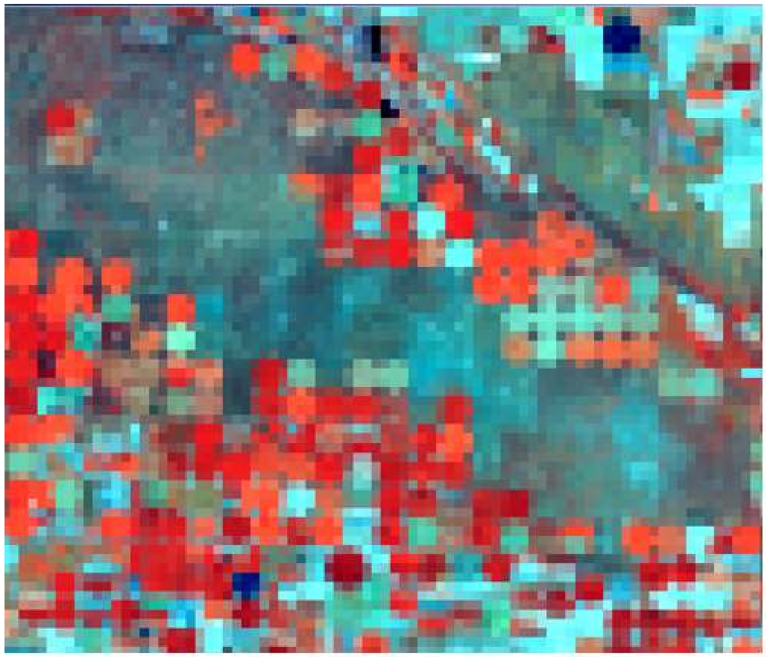

Figure 1.1 Sample MODIS 250m resolution image (false color composite).

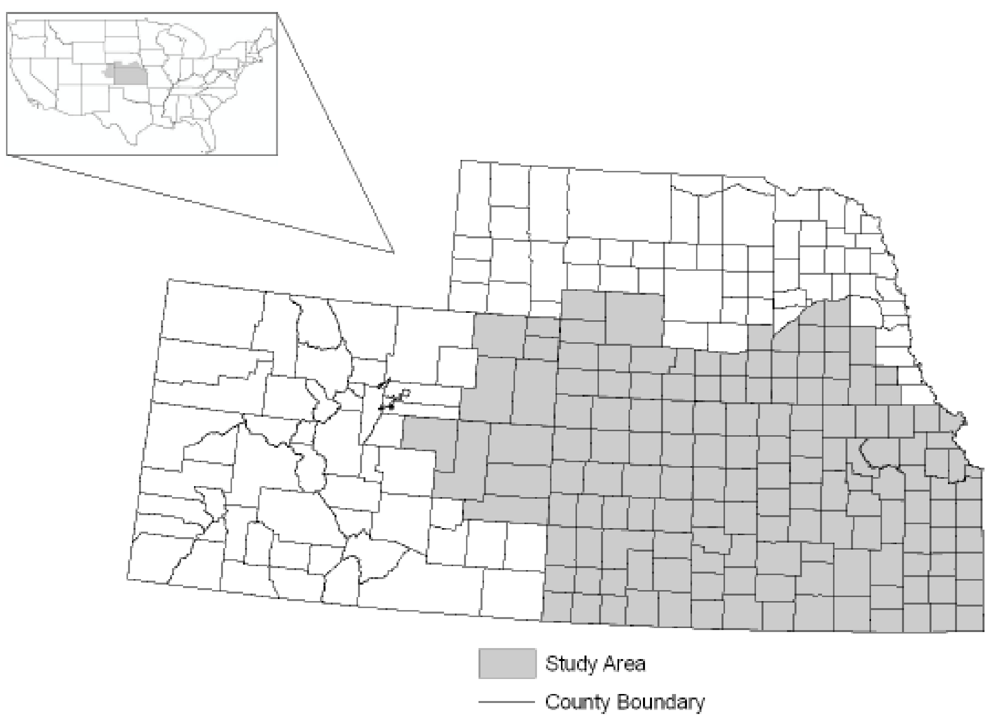

Figure 1.2 Study Area including the State of Kansas and Kansas River Basin.

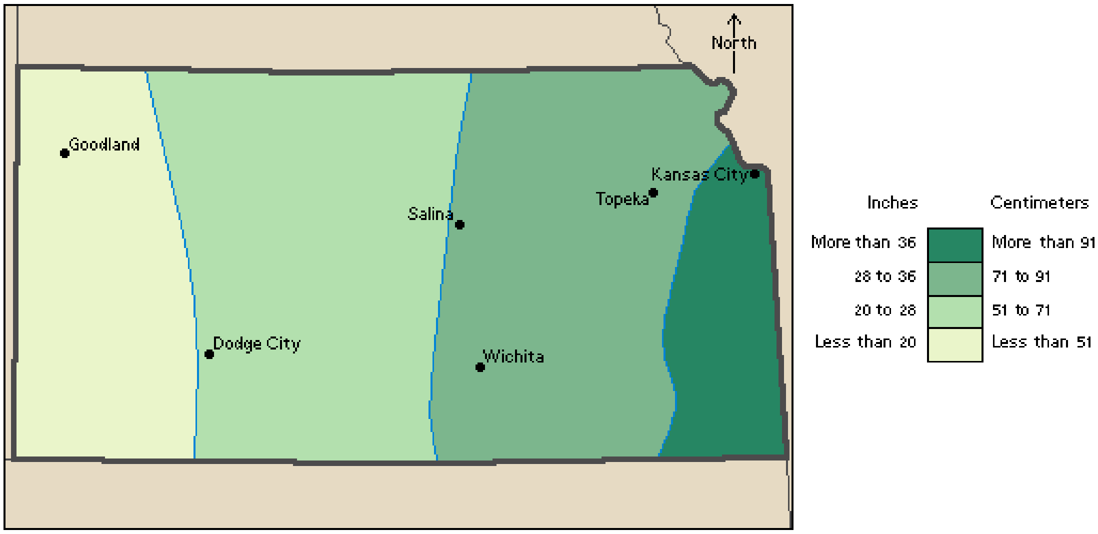

Figure 1.3 Pronounced east-west precipitation gradient in the state of Kansas (2010 World Book).

Chapter 2

CROP MAPPING USING TIME-SERIES MODIS 250-METER VEGETATION INDEX DATA: A STATE-WIDE STUDY OF KANSAS AND THE KANSAS RIVER BASIN

2.1 INTRODUCTION

Agricultural landuse/landcover data are among the most important and universally used terrestrial spatial data sets (IGBP, 1990). Up-to-date maps and data sets that map specific crop types are needed over intensively cropped regions for applications focused on understanding the role and response of the agricultural sector to environmental change issues (Wardlow et al, 2007). The cropland component of the agricultural landscape is of specific interest because it is intensively managed and has dynamic land cover patterns. Cropland patterns are continually modified by a wide range of human activities like crop rotations and fallowing as well as the introduction of new crops or discontinuation of former crops. As a result, detailed regional-scale cropping patterns need to be mapped on a repetitive basis in order to characterize dynamic land use/land cover patterns and monitor common changes (Wardlow, et al 2007).

Landcover Mapping

Regional to continental-scale land cover mapping using wide-field sensors has been done since the mid-1980s. Initial Advanced Very High Resolution Radiometer (AVHRR) derived land cover classifications were produced for Africa (Tucker *et al.*,

1985) and South America (Townshend *et al.*, 1987) using multi-temporal NDVI data. DeFries and Townshend (1994) generated an 11-class, 1-degree resolution global land cover map from monthly composited NDVI data in support of climate modeling. DeFries *et al.* (1998) improved upon this effort by creating a 13-class global land cover map from the same data set. Loveland *et al.* (1991) derived the first complete land cover map for the conterminous U.S. using 1-km multi-temporal AVHRR NDVI data. In Loveland et al.'s work, seasonal land cover regions (i.e., those that exhibit unique phenological characteristics and represent relatively homogeneous vegetation associations) were classified from a time series of monthly composited NDVI data and other ancillary data sources (e.g., climate and terrain variables). Loveland *et al.* (1999) applied this classification concept globally to produce a similar 1-km global, multidimensional land cover database. Hansen *et al.* (2000) built upon the previous 8-km work of DeFries *et al.* (1998) and generated a global, 14-class general land cover map using a 12-month time-series of monthly composited 1-km AVHRR data. Currently an operational, global 1-km land cover product is being produced annually from multi-temporal, multi-spectral MODIS data (Friedl *et al.*, 2002). In recent years, the application of MODIS data for landuse/landcover mapping has become widespread (Wardlow and Egbert, 2007; Xiao *et al*., 2006; Xavier *et al*., 2006).

Mapping Kansas Croplands

The study area for this research is Kansas and the Kansas River basin. Brian Wardlow (Wardlow, 2005) and Iwake Masialeti (Masialeti, 2008), in particular, have used MODIS NDVI data to map croplands in the state of Kansas for individual years. For his dissertation research, Wardlow mapped croplands in Kansas for 2001 and has published articles based on this research (Wardlow and Egbert 2007; Wardlow et al 2007). Wardlow classified his 2001 cropland data using training site data gathered from USDA Farm Service Agency (FSA) crop photographs. He concluded that croplands in the Great Plains could be accurately mapped using time series MODIS 250m vegetation index data. Masialeti built on Wardlow's work by analyzing NDVI time-series curves for Kansas crops in 2005 for his dissertation research. To date, Masialeti's 2005 dataset has not been classified but does include Common Land Unit (CLU) based training data.

MODIS

The datasets that were utilized for this study are derived from Moderate Resolution Imaging Spectroradiometer (MODIS) imagery. The guiding philosophy behind the MODIS design was to collect daily coverage of well calibrated multi-spectral, multi-resolution imagery from which higher-level quality data sets could be generated to meet the needs of the global change research community. Designed for land, oceanic and atmospheric applications, MODIS adopted a multi-spectral approach by incorporating 36 spectral bands, which cover the visible through long-wave infrared regions. Seven bands were carefully selected to capture the key spectral features of terrestrial targets, and their bandwidths were narrowed to avoid atmospheric absorption regions, particularly for the near infrared band (Justice *et al.*, 1998). MODIS has a radiometric resolution of 12-bits for improved sensitivity to subtle spectral differences. MODIS also includes several atmosphere-related bands that measure cloud properties, aerosols, and water vapor, which are used to rigorously correct for atmospheric constituents and enable accurate surface reflectance values to be calculated (Justice *et al.*, 1998). Spectrally, MODIS contains two 250-m (red and NIR), five 500-m (blue, green, and MIR), and twenty-nine 1-km bands. The 250-m bands allow for the detection of human-induced land cover changes, many of which were found to occur at or near this spatial scale (Townshend and Justice, 1988). With the 250-m imagery, most individual fields of the Central Great Plains are large enough to be represented by multiple pixels (usually a minimum of 5 pixels). The high temporal resolution (16-day composite period) of the time-series data is also favorable for discriminating crop types based on their unique crop calendars (phenology). MODIS also includes a 250-m Normalized Difference Vegetation Index (NDVI) data set.

NDVI

The cropland datasets for this study were compiled using a time-series of NDVI data. NDVI is a transformation that capitalizes on the differential responses of the visible red (absorbed by chlorophyll pigments) and NIR (reflected by the spongy mesophyll structure of leaves) spectral regions to vegetation and takes the form: NDVI = (NIR – red) / (NIR + red) (Rouse *et al.*, 1974). NDVI is a dimensionless, radiometric measure of green vegetation amount/condition that has been related to several biophysical variables such as biomass, Fraction of Photosynthetically Active Radiation (FPAR), and Leaf Area Index (LAI) (Asrar *et al.*, 1989; Baret *et al.*, 1991). NDVI provides a normalized range of values (-1 to +1) that are directly comparable over both space and time. In order to obtain relatively cloud-free global images, daily observations are composited over a defined time interval (Strahler *et al.*, 1999). A monthly composite period is typically used for global applications, while more localized studies utilize a shorter temporal window (e.g., 10-day or bi-weekly). It is these NDVI composites that have become the standard input for landcover mapping past and present.

2.2 RESEARCH OBJECTIVES

The purpose of this study was to use 250-meter MODIS NDVI time-series data to map the seven major crop classes (corn, soybeans, sorghum, winter wheat, alfalfa, fallow, and double crop) for the state of Kansas for 2005. USDA CLU data were used for training and validation. This study was part of the larger Kansas Next-Generation Land Use/Land Cover Mapping Initiative that was conducted by the Kansas Applied Remote Sensing Program and the Kansas Biological Survey. The purpose was to update the land use database which was 15+ years old. The classification and mapping protocol used in this study followed the one established by Wardlow in 2005. The main objective of this research was to determine what level of classification accuracy could be achieved for 2005 using training data from the 2005 USDA Common Land Unit (CLU) dataset.

More specific questions this research addressed include: (i) How does this CLU based classification compare to Wardlow's 2001 classification that used training data derived from FSA crop photo data? (ii) Do any regional variations or major misclassifications exist compared to the USDA reported crop acreage and patterns? (iii) What effect does the absence of training and validation data for parts of the study area have on classification accuracies? Does this lead to more variation and misclassification?

2.3 STUDY AREA

This study was conducted in the state of Kansas along with the expanse of the Kansas River Basin in portions of Nebraska and Colorado (Figure 2.1).

Kansas

The Kansas landscape is dominated by a cropland/rangeland mosaic with 46.9% (10.0 million ha) of its total area intensively cropped (Wardlow, 2005). The state's major crop types include alfalfa (*Medicago sativa*), corn (*Zea mays*), sorghum (*Sorghum bicolor*), soybeans (*Glycine max*), and winter wheat (*Triticum aestivum*). The state's pronounced east-west precipitation gradient strongly influences the specific cropping patterns and associated management practices. On average, western

Kansas receives 457-505 mm (18-20 inches) of precipitation per year while eastern Kansas receives 889-1016 mm (35-40 inches) per year (USDA, 2002).

In semi-arid western Kansas, extensive irrigation from groundwater sources (i.e., the Ogallala and Dakota aquifers) and dryland farming techniques (e.g., crop-fallow rotations and no-till farming) maintain high crop production levels despite the area's limited precipitation regime. Approximately 21% (0.9 million ha) of the area's cropland is irrigated and primarily supports alfalfa, corn, and soybeans (USDA, 2002). The remainder of western Kansas is non-irrigated due to inaccessibility of groundwater or financial considerations. Most non-irrigated areas are planted to dryland crops such as sorghum or winter wheat or remain fallow some years to conserve soil moisture for crop production the next year. The increasing adoption of no-till farming (direct planting of a crop into the crop stubble/residue from the previous year) as a soil moisture conservation technique has resulted in higher yields from traditional dryland crops, increased the acreage of crops with higher water requirements (e.g., corn) in historically non-irrigated areas, and lessened the reliance on crop-fallow rotations (Wardlow, 2005). In eastern Kansas, adequate precipitation is generally received to support high crop production levels without irrigation. Corn and soybeans are the dominant crops in the east and fallow land use practices are rare. Irrigation is very limited in eastern Kansas and is primarily applied in lowland floodplain areas where groundwater is readily accessible.

On average, Kansas has led the nation in both winter wheat and sorghum area (26.0% and 43.7% of the nation's total, respectively) and production (23.6% and

41.3% of the nation's total, respectively) (NASS, 2004). The economic importance of the state's cropland sector is reflected by its $3.6 billion in crop production in 2004, which ranked sixth nationally (NASS, 2004).

The average parcel size, or "grain", of the landscape also changes from western to eastern Kansas. Western and central Kansas are characterized by a coarse-grained landscape comprised of very large individual fields and large contiguous areas of both cropland and grassland or shrubland areas (Wardlow, 2005). Field sizes commonly range from 65 to 245 ha (160 to 600 acres). In contrast, cropland areas in eastern Kansas are more fragmented and interspersed with other land cover types (e.g., deciduous forest and grassland). Individual fields are also smaller, with most fields being 65 ha (160 acres) or less.

Nebraska

Most of Nebraska south of the Platte River, 16,916 square miles (43,812 km^2), is part of the Kansas River basin (Colby et al., 1956). This region of Nebraska is characterized by a north-to-south decrease in elevations and increase in temperature as well as an east-to-west decrease in mean precipitation. Precipitation averages range from 360 mm (about 14 in) annually in the west, to more than 860 mm (34 in) in the east.

Most of south central Nebraska is composed of loess plains and is farmed intensely. Corn is the dominant crop followed by soybeans and winter wheat. Southwestern Nebraska lies in the High Plains which are characterized by a large expanse of high flat tableland. This area receives little rainfall but some farming is accomplished with the use of center-pivot irrigation. The growing season ranges from 130 days in the west to more than 170 days in the east. Farmland occupies 18.5 million hectares (45.6 million acres), of which 47 percent is cropland. Some 34 percent of the cropland (mostly used to grow corn) is irrigated. The agricultural landscape consists of a mosaic of relatively large fields, with an average farm size of 388 ha (980 acres) (USDA, 2007).

Colorado

In addition, 8,775 square miles (22,727 km^2) in northeast Colorado is part of the Kansas River basin (Colby et al., 1956). The Eastern Plains of northeast Colorado are part of the High Plains, which are the westernmost portion of the Great Plains region. This section is some 150 miles (240 km) wide and covers more than a third of the state. It consists mainly of level to rolling land that slopes gradually upward to the foot of the Rocky Mountains. Elevations vary from about 3,400 feet (1,040 m) along the state's eastern border to as much as 6,000 feet (1,830 m) at the edge of the Rockies. The Eastern Plains have a semi-arid climate, like all of the High Plains, but receive lower rainfall than areas to the south and east. Rainfall is meager, averaging about 15 inches (380 mm) annually. The growing season ranges from 120 to 200 days on the plains. Farmland occupies 12.7 million hectares (31.3 million acres), of which 36 percent is used to grow crops. Winter wheat is the dominant crop and corn is the second most important crop grown in Colorado. There is some irrigated farming, but much of the land is used for dryland farming. Because annual rainfall fluctuates, the greater part of the plains is often too dry for cultivation every year. Therefore fallowing land and other forms of soil and water conservation are important.

2.4 DATA AND PREPROCESSING

Time-Series MODIS NDVI and Landsat TM Data

A 12-month time-series of MODIS 250-meter NDVI data from the year 2005 was used. This was compiled by the Kansas Applied Remote Sensing Program for the State of Kansas and areas of the Kansas River basin that extend into Nebraska and Colorado. Three MODIS tiles (09v05, 10v05, 10v04) were needed to cover the entire study area. The data was mosaicked by a 16-day composite period and reprojected to the USGS Albers Equal Area projection. The mosaics were then stacked to create 23 time-series periods from January 1 to December 19, for 2005.

Landsat TM imagery from the 2004-2005 Kansas Satellite Image Database (KSID) (Whistler *et al.*, 2006), a database previously developed by the Kansas Applied Remote Sensing Program and funded by the Kansas State GIS Policy Board with assistance from the USGS AmericaView program, was the primary data source used for the development of the Level I statewide land cover map (Figure 2.2). This map was derived using three-date multi-seasonal (spring, summer, and fall) Landsat Thematic Mapper (TM) imagery and an unsupervised classification approach. The Level I map includes general landcover classes including cropland.

Field Site Database

A training and validation database of field site locations of specific crop types was created using USDA Common Land Unit (CLU) boundary and attribute data. A CLU boundary is the smallest unit of land that has a permanent, contiguous boundary, a common land cover and land management, a common owner and a common producer in agricultural land associated with USDA farm programs (FSA, 2008). CLU boundaries are delineated from relatively permanent features such as fence lines, roads, and/or waterways. CLU data were available for 64 of the 105 Kansas counties (Figure 2.4).

The National Agricultural Imagery Program (NAIP) provides FSA with 9" by 9" large format color digital imagery at 1:40,000 scale (Williams, 2004). The NAIP imagery is used to maintain CLU data continuously in the USDA county-based Field Service Centers. CLUs are also used to generate agricultural training and validation data used in producing the USDA NASS Cropland Data Layer (CDL) (Allen *et al*., 2002). For this research, Masialeti's (2008) field sites (a total of 1,254) were used. Masialeti's field sites did not contain any fallow or double crop sites so those were extracted from the CLU attribute data using the same methodology and protocol as Masialeti. Only fields 32 ha (80 acres) or larger were used. This amounts to approximately five 250-m MODIS pixels per field site. Any irregularly shaped fallow and double crop fields were removed. It was necessary to remove irregularly shaped fields to assure that at least one entire 250-m MODIS pixel fell within each field's boundary. To remove irregularly shaped fallow and double crop fields, a shape index was calculated. This was done by dividing the field's area by the perimeter. Only fields with an index higher than 35 were used.

A single 250-m pixel located completely within each field's boundary was selected to represent each site. The NDVI profile associated with the pixel was then extracted from the time-series MODIS data. The extracted NDVI data from the initial field sites for each crop type were subjected to Cluster Analysis (Romesburg, 2004), using *k-means* clustering, as a way of evaluating variability among field sites within each crop type, and to identify and eliminate outliers. Following Masialeti's protocol, 10 clusters were used. The field sites were then analyzed to determine if they fell within the cropland mask from the level 1 map. Those sites falling outside of the areas designated as cropland were eliminated. This processing resulted in 1442 final field sites (1173 of Masialeti's plus an additional 171 Fallow and 98 Double Crop) (Figure 2.5).

NASS Statistical Database

Planted crop acreage data for 2005 were obtained from the USDA NASS agricultural statistics database (http://www.nass.usda.gov) (NASS, 2006) for the study area. For Kansas, this data set was acquired at both the state and Agricultural Statistical District (ASD) level. Areas of the Kansas River basin outside of Kansas were acquired at the county level. The planted crop acreage reported by NASS is a statistical 'estimate' calculated from crop information provided by farmers and field enumerators from a probability-based sample survey (USDA, 1999). Since the NASS reported acreages are estimates, they should be considered only a relative measure of the actual cropping patterns in the study area. The NASS planted acreages were reported by specific crop type, including corn, soybeans, sorghum, winter wheat, and alfalfa. The USDA NASS agricultural statistics database does not contain any information on acreage for fallow or double crop cover types.

2.5 METHODS

Decision Tree Classifiers

Decision tree (DT) classifiers are increasingly being used for remote sensing LULC classification problems and currently serve as the main classification algorithm for prominent national- and global-scale LULC mapping efforts such as the USGS NLCD (Homer *et al.*, 2004) and the MODIS Land Cover Type product (MOD12Q1) (Friedl *et al.*, 2002). DTs are non-parametric, hierarchical classifiers that predict class membership by recursively partitioning data sets into more homogeneous, mutually exclusive subsets via a series of internal nodes (Wardlow, 2007). At each internal node, all possible thresholds of all independent variables are examined and the specific threshold of a single variable is selected. The variable that is selected will be the one that results in the most homogeneous subset based on statistical deviance (Wardlow, 2007). This is then selected to separate the data into two exclusive subsets.

This procedure is repeated to produce more homogeneous subsets. This process continues until a tree is created where each node contains training observations from a single class. Once the DT's classification structure is established, each observation (pixel) from the unseen image data is passed through the tree and assigned to the class of the leaf node into which it falls (Wardlow, 2007).

DTs offer several advantages over traditional supervised classifiers. Since DTs are 'non-parametric' there are no assumptions regarding the distributions of the input data. In addition, they recognize a variety of data types (categorical, hierarchical, numeric) and are well suited for dealing with noise or gaps in the data. DTs also have several additional features incorporated to improve classification accuracies over traditional supervised classifiers.

'Pruning' is a key feature that has typically been incorporated into the DT classification process for LULC mapping applications in order to make the tree's predictive ability more robust when applied to unseen data (Hansen *et al.*, 1996; Friedl and Brodley, 1997; DeFries and Cheung-Wai Chan, 2000, Friedl *et al.*, 2002; Homer *et al.*, 2004). Pruning involves removing parts of the tree (i.e., internal nodes) that are predicted to have a relatively high error rate or contribute little to reducing the deviance in the training data.

'Boosting' is an ensemble classification technique developed in the machine learning community (Shapire, 1990) that has recently been incorporated with DT classifiers for LULC classification (Friedl *et al.*, 1999; DeFries and Chan, 2000). The purpose of boosting is to generate several classifiers (i.e., decision trees) rather than a single classifier, to improve the accuracy of the base classification algorithm. Boosting estimates multiple classifiers from a base classification algorithm in an iterative fashion while systematically varying the training sample through reweighting or a resampling procedure. The final 'boosted' classification output is produced by a weighted voting scheme across the multiple classifiers. Any number of iterations can be performed, but previous work using both non-remote sensing (Freund and Schapire, 1996) and remote sensing data (Friedl *et al.*, 1999) has shown that improvements in classification accuracy are minimal after 7 to 10 iterations. For most previous LULC mapping efforts that have applied boosting (Friedl *et al.*, 1999; DeFries and Chan, 2000; McIver and Friedl, 2001), 10 iterations were used.

Mapping Methodology

The cropland class from the Level I map was used as a mask to identify and isolate cropland areas in the MODIS imagery. Cropland includes all areas with actively growing row crops and small grains, as well as harvested lands, fallow land, and large, uniform areas of bare, plowed ground. Each crop map was produced by applying the supervised See5 DT classification algorithm (including the boosting and pruning options) to the time-series MODIS NDVI data. The field sites provided by the USDA CLU were used to train the DT classifier and validate the crop maps. The specific crop classification methodology consisted of three steps established by Wardlow. The field site data were divided into training (80%) and validation (20%) data sets using a stratified random sampling scheme.

To create the crop maps the See5 decision tree classifier then was applied to the time-series MODIS 250-m NDVI data to produce the three crop-related LULC maps (general, summer crops, all crops). The See5 decision tree classifier was applied to map the following cropland subclasses: summer crops, winter wheat, alfalfa, double crop, and fallow land. The cropland pixels in the Level I map were reassigned to each cropland subclass creating a Level 2 map. Summer crops from the Level 2 map were then used as a mask to identify and isolate summer crop areas in the MODIS imagery. Again the See5 decision tree classifier was used to map the following summer crop subclasses: corn, soybeans, and sorghum. The Level 2 (general crops) map was then reclassified substituting corn, soybeans, and sorghum for the summer crops class. This end result is a Level 3 crop map containing all 7 classes.

The specific growing season window used for each crop classification was based on prior research by Wardlow in which he defined the window by the phenology (crop calendar) of its respective target classes. The spectral-temporal behavior of each crop's time-series profile corresponded well with its reported crop calendar (Figure 2.6). For the general crop classifications, the growing season was defined from the March 22 to November 1 composite period (15 periods). For the summer crop classification, a shorter window was defined from the April 7 to October 16 composite period (13 periods). With both the general and summer crop classifications, the sampling procedure was repeated 10 times and then a separate classification was performed with each training dataset to produce 10 separate maps.

Lastly, the 10 maps were ‘stacked’ and a pixel-level ‘majority vote’ was taken across the 10 maps to produce the final map. This multiple classification run and majority voting approach was used to avoid the misclassification that would likely result from a single random draw of training and validation data. Since a stratified random sample is drawn, with only one draw there is a chance that an unusual sample could be drawn. This could affect either the entire dataset or a specific class. Both could result in a poor classification.

A separate accuracy assessment was conducted for each map using its respective validation data set. Areal comparisons between the classified crops in the final maps and the USDA crop planted figures were conducted at both the state and ASD levels. The classified crop patterns of the final maps were also visually assessed and compared to the state’s reported cropping patterns.

2.6 RESULTS AND DISCUSSION

The original mapping protocol called for an area-wide classification for the entire study region. However, after an initial area-wide classification was completed, the desired level of accuracy was not achieved. Therefore the decision was made to use a revised mapping protocol where classifications were conducted at a finer scale. As previously noted, a pronounced precipitation gradient exists from west to east. This pronounced gradient likely has an impact on the crops’ phenology, resulting in temporal variations in greenup and other growth stages across the study-area. Taking these factors into consideration, the study area was divided into three sections: west, central, and east (Figure 2.7). Using these newly defined subsets, three separate classifications were performed. Upon completion, the three subsets were combined to reconstitute the original study-area.

General Crop Classification

Visual Assessment

A visual assessment of the general crop map (Figure 2.8) revealed that the crop patterns were consistent with the general cropland patterns found throughout the study area. The summer crop class was dominant in eastern Kansas and the Nebraska portion of the study area. This would be consistent with the Corn Belt region. Note that the western-most extent of the Corn Belt in west-central Nebraska can clearly be seen. In central and western Kansas the mapped winter wheat areas clearly correspond to the Winter Wheat Belt. An area of summer crops exists in north-central Kansas in the lowland areas surrounding the Republican River as expected. Note the irrigated cropland in southwest Kansas (ASD 30) planted to summer crops. There is also an area of irrigated alfalfa.

It is important to note the fallow land in western Kansas. On a yearly basis, as much as 30% of the cropland in this area sits fallow. Notice that in Colorado there is an even higher concentration of fallow land. This has likely been over-classified due to the lack of training or validation data for this part of the study area. It appears that cropland in general has been overestimated from the Level 1 classification in Colorado. This would explain the large amount of fallow landcover depicted by the map. Many of the areas mapped as fallow are likely grassland. Note the high concentration of double crop found in the southeast corner of Kansas (ASD 90). This is mainly winter wheat followed by soybeans. Visually, it appears that the double crop class has been over-classified. Based on the known cropping patterns, double crop is mainly limited to southeastern Kansas and irrigated fields in the southwest (ASD 30) and the south-central (ASD 60). Yet the classified map shows sporadic areas of double crop in other regions of the study area.

Areal Comparison

A relatively high level of agreement was found between the map and the USDA reported acreage (Table 2.1 and 2.2). A consensus exists between the map and the USDA statistics that wheat and summer crops are the dominant crops with essentially the same coverage (about 10 million acres each) in the study area. These are followed by fallow, alfalfa, and double crop. While the USDA statistics do not contain reported acreages for fallow and double crop, this is consistent with the cropping practices for the study area.

ASD-level comparisons revealed a relatively high overall correlation (r) of 0.86 between the map and the USDA reported acreage for general crop classes. Wheat had the highest correlation (r=0.97) followed by summer crops (r=0.91), and alfalfa (r=0.84). Alfalfa had a lower correlation due to the moderate over-classification of alfalfa (+6.8%) in ASDs 40 50 and 60 in central Kansas. Moderate under-classifications of alfalfa (-3.2%) occurred throughout the Colorado portion of the study area. Even though wheat has the highest correlation, moderate (-5.1%) to major (-10.8%) under-classifications still exist. This is the case throughout Kansas' eastern districts (ASDs 70, 80, and 90). The variation in ASD 90 is likely due to the fact the some of the area planted to wheat was classified under the double crop class. A moderate under-classification (-3.6%) also exists in southeast Nebraska.

Statistical Accuracy Assessment

The general crop map had a relatively high overall accuracy of 82.4% (Table 2.3). The user's and producer's accuracies for specific classes ranged from 86.3% (summer crops) to 66.7% (double crop). Summer crops and winter wheat had relatively high overall class accuracies while the alfalfa, fallow and double crop classes did not fare as well. Based on the error matrix, the following misclassifications were observed: (1) summer crops were occasionally classified as wheat, (2) wheat was occasionally classified as summer crops or fallow, (3)alfalfa was frequently classified as winter wheat and summer crops, (4) fallow was frequently classified as winter wheat, and (5) double crop was frequently classified as alfalfa and summer crops.

The NDVI curves for summer crops and winter wheat are vastly different; in fact, they are nearly the reverse of one another (Figure 2.6). These misclassifications are likely due to an error in the training sites where either summer crop sites were actually winter wheat sites or winter wheat sites where actually fields where summer crops were grown. It is likely that alfalfa was frequently classified as winter wheat because they share nearly identical NDVI values during the early part of the growing season (March thru June) (Figure 2.6). Alfalfa was also classified as summer crops. Alfalfa and summer crops have dissimilar NDVI response curves. As a result, there is a possibility that some of the alfalfa training sites were actually summer crop training sites. A potential reason why fallow was frequently classified as winter wheat is due to the presence of weeds growing on the fallow land. This would lead to NDVI values more similar to those of winter wheat thus causing some confusion. Lastly, it is probable that double crop was classified as alfalfa because they share very similar NDVI values throughout the growing season. Remember double cropping practices consist of winter wheat followed by a summer crop (usually soybeans). If the NDVI curve for alfalfa is compared to the winter wheat curve followed by soybeans they appear quite similar (Figure 2.6). Double crop was also frequently classified as summer crops. This is likely due to the fact that double crop contains a summer crop, hence the confusion.

Summer Crop Classifications

Visual Assessment

A visual assessment of the summer crop map (Figure 2.9) found that the specific summer crops were consistent with known summer cropping patterns for the study area. Summer crops are planted at relatively different times. Corn is typically the earliest planted summer crop in the study area (April to mid-May) followed by soybeans (mid-May to mid-June) and sorghum (late-May to late-June) (Shroyer *et al.*, 1996). The Corn Belt region is clearly defined throughout the Nebraska portion of the study area and in northeastern Kansas (ASD 70). Note the large amounts of corn with soybeans intermixed in Nebraska. Corn and soybeans were the main summer crops mapped in eastern Kansas and Nebraska, which is consistent with the known cropping practices. The map clearly shows a transition to sorghum as the dominant summer crop in the west. Sorghum is the most common summer crop in dryer more arid regions like western Kansas and eastern Colorado. Notice the sliver of corn in north-central Kansas (ASD 40) which corresponds to the Republican River valley. Also note the areas of soybeans and corn growing in the Kansas River valley along the borders of ASD 70 and ASD 80 in east-central Kansas.

Areal Comparison

A fairly high level of agreement was found between the classified and USDA summer crop areas at the state level for Kansas (Table 2.4 and 2.5). There was a consensus between the map and the USDA statistics that corn is the dominant summer crop with roughly 9 million acres. Corn is followed by soybeans and sorghum. ASD-level comparisons revealed an overall correlation (r) of 0.84 between the map and the USDA reported acreage for the summer crop classes. Correlations were relatively high for corn (r=0.96) and soybeans (r=0.89) but considerably lower for sorghum (r=0.67). This is likely due to the major over-classification of sorghum in northeastern Colorado (+33.0%), eastern Colorado (+15.7%), and Southwestern Nebraska (+8.9%). Major under-classifications occurred in central Kansas in ASD's 50 (-15.7%) and 60 (-13.6%) The greatest variation between the map and USDA statistics for corn came in the central part of the state of Kansas. A major over-classification of corn occurred in ASDs 50 (+20.2%) and 60 (+19.7%) with a moderate over-classification in ASD 40 (+9.0%). Major over-classifications of soybeans exist in the west in ASDs 10 (+13.3%) and 20 (+13.0%) with a moderate over-classification in ASD 30 (+8.3%). A major over-classification of soybeans also occurred in southwest Nebraska (+11.4%). A major under-classification (-14.2%) of soybeans exists in ASD 90. The variation in ASD 90 is likely due to the fact that some of the area planted to soybeans was classified under the double crop class.

Statistical Accuracy Assessment

The summer crop map had a relatively high overall accuracy of 80.6% (Table 2.6). The user's and producer's accuracies for specific classes ranged from 85.8% (corn) to 72.4% (sorghum). The class specific accuracies for corn and soybeans were both fairly good considering both are >80%. However, the class-specific accuracies for sorghum are only >70%. Based on the error matrix, the following misclassifications were observed: (1) corn was occasionally classified as sorghum and soybeans, (2) soybeans were occasionally classified as corn, and (3) sorghum was frequently classified as corn.

It is likely that corn was sometimes classified as sorghum and soybeans because their NDVI curves are almost identical during the early stages of the growing season (April thru June) (Figure 2.6). There was also some confusion where soybeans were classified as corn. Again, this is likely due to the very similar NDVI values they share early in the growing season. There was significant confusion between sorghum and corn where sorghum was frequently classified as corn. Some of this can be explained by the closely matching NDVI values early in the growing season (Figure 2.6). However, their values during the peak of the growing season (July thru September) were significantly different. This leads to the assumption that some of the sorghum training sites might have actually been located on corn fields.

A final Level 3 map product (Figure 2.10) containing all 7 crop types was created by reassigning the summer crop map to the summer crop class on the general crops map.

Comparison to Wardlow's 2001 Classified Map

A relatively high level of agreement was found between both series of maps. The known general and summer cropping patterns for the state were clearly defined by both Wardlow's 2001 map and my 2005 map. The most obvious difference is the variation in overall accuracy. Wardlow's 2001 general crops map had an overall accuracy of 93.9% (Table 2.9) compared to 82.4% for my 2005 general crops map. However, there was less variation between the summer crops maps. Wardlow's 2001 summer crops map had an overall accuracy of 84.0% (Figure 2.10) compared to 80.6% for my 2005 summer crops map.

There are several factors that likely led to the overall lower accuracy of the 2005 classified maps. All of these factors are related to the training data. First, the training data are from different sources. Wardlow's sample sites were derived from FSA aerial photographs while 2005 sample sites were generated using CLU data. Wardlow generated his own sites while the 2005 sample sites were drawn from the CLU database. With the CLU database, there is room for user error. For instance, the wrong data could be entered in the database during the data-entry process. In addition, the farmers themselves could report mistaken information to the USDA regarding what CLU's are planted with what crop type.

A second factor to consider is the variation in the distribution of the training sites. With the 2005 training sites (Figure 2.4) only 64 counties were included in the CLU database. As a result, there is more of a clustering to the sites compared to Wardlow's 2001 training data (Figure 2.10). The majority of the 64 counties included in the CLU database fell in the western half of the state. As a result, there was a higher concentration of sample sites in these areas whereas Wardlow's sample sites were more evenly distributed throughout the state. One final factor regarding the variation in accuracy between the two maps is the number of sample sites. Wardlow used 2,205 total sample sites for 2001 compared to 1,442 for the 2005 map. Not only does the overall number vary but there is also variation by individual crop class.

2.7 CONCLUSIONS

The results of this study have demonstrated that the MODIS-based mapping protocol established by Wardlow is an acceptable option for accurate regional crop mapping in the central U.S. The LULC crop maps had a relatively high classification accuracy (82% for the general map and 81% for the summer map). The crop patterns were consistent with the cropping patterns of the region and reported crop statistics. The diverse range of environmental conditions across the region, however, likely impacted the classification results. Most notable is the east-west precipitation gradient. While measures were taken to attempt to alleviate this impact by making adjustments to the mapping protocol, it likely still influenced the results. The smaller fragmented fields found in the eastern portion of the study area did not appear to cause any significant classification problems at the 250-m resolution. These classification accuracies were consistent with those found in the coarse-grained west where field sizes were significantly larger. The greatest misclassifications (based on areal assessment) were found to be in Colorado. This is likely due to the lack of training and validation sites for this portion of the study area.

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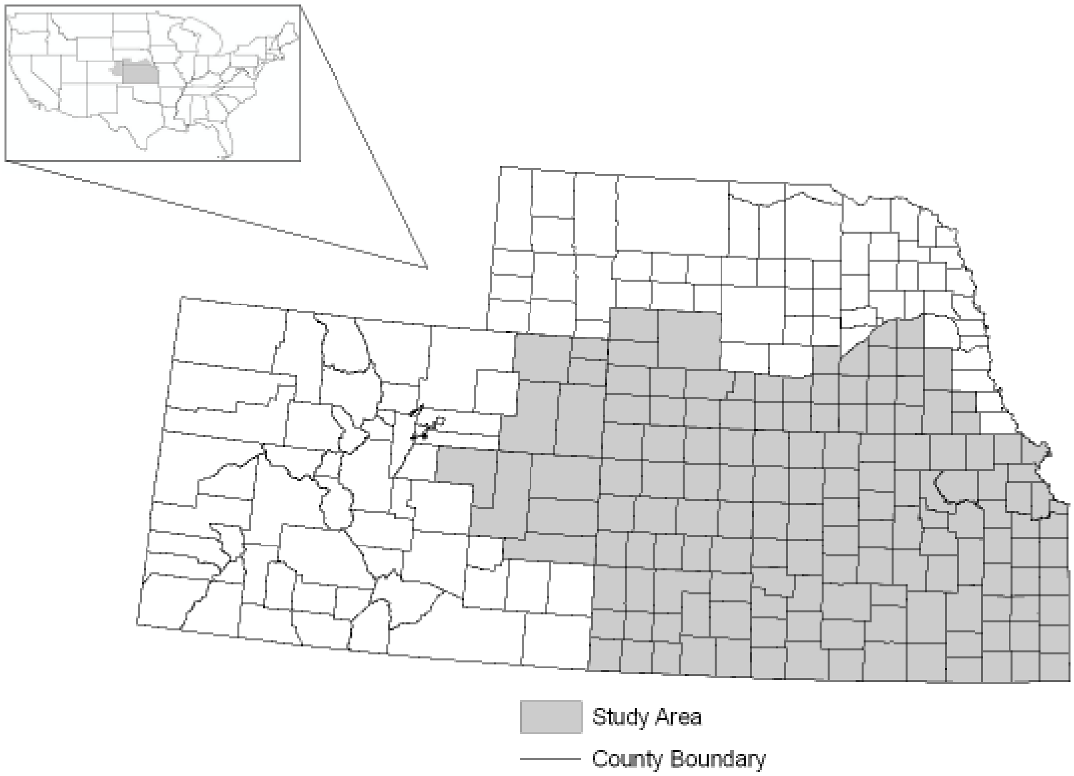

Figure 2.1 Study Area including the state of Kansas and the Kansas River Basin.

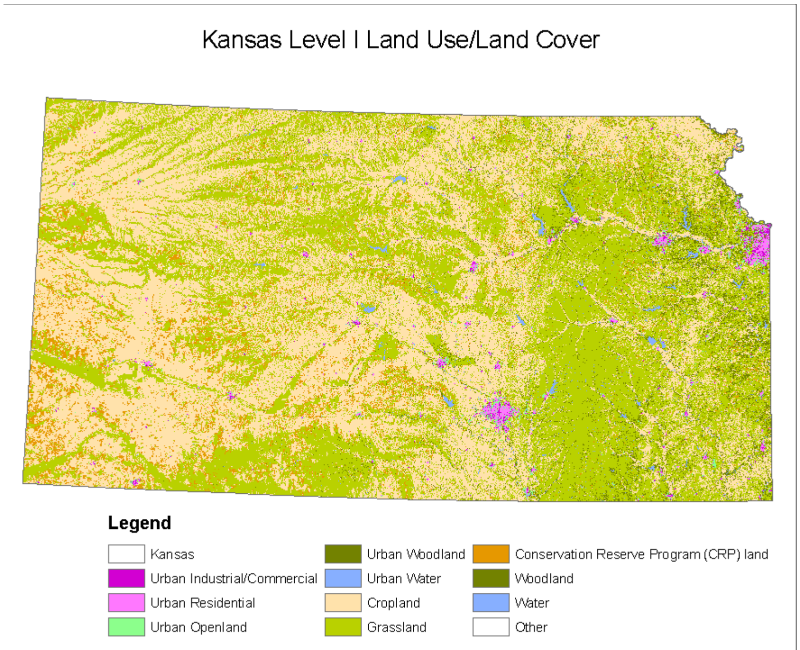

Figure 2.2 2005 Kansas land cover patterns level 1 map (KARS).

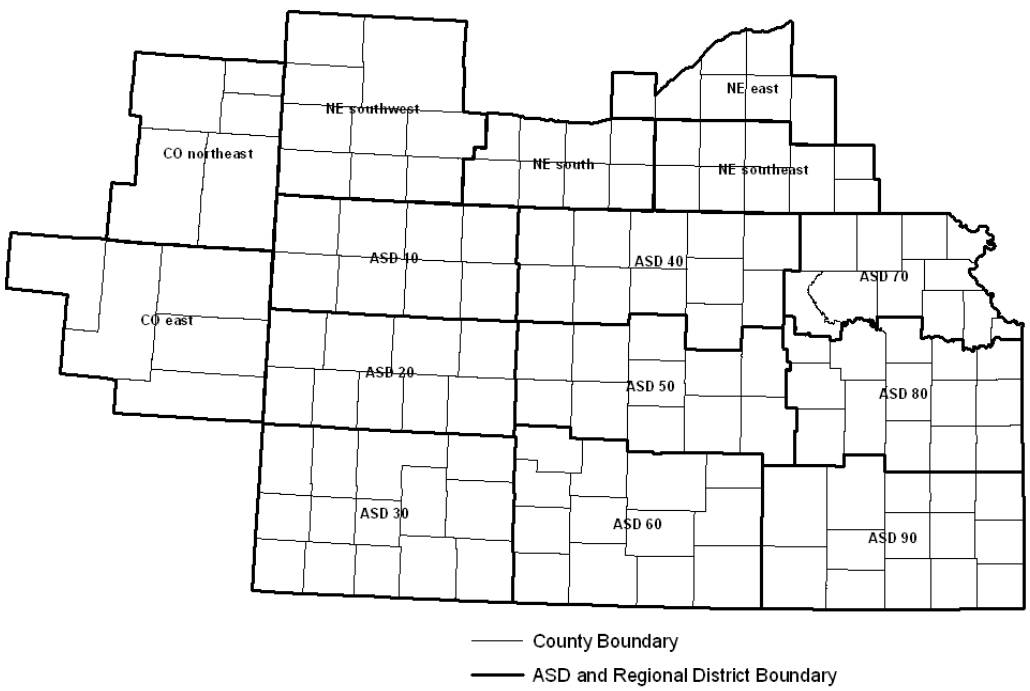

Figure 2.3 Study Area segmented by ASDs and regional districts.

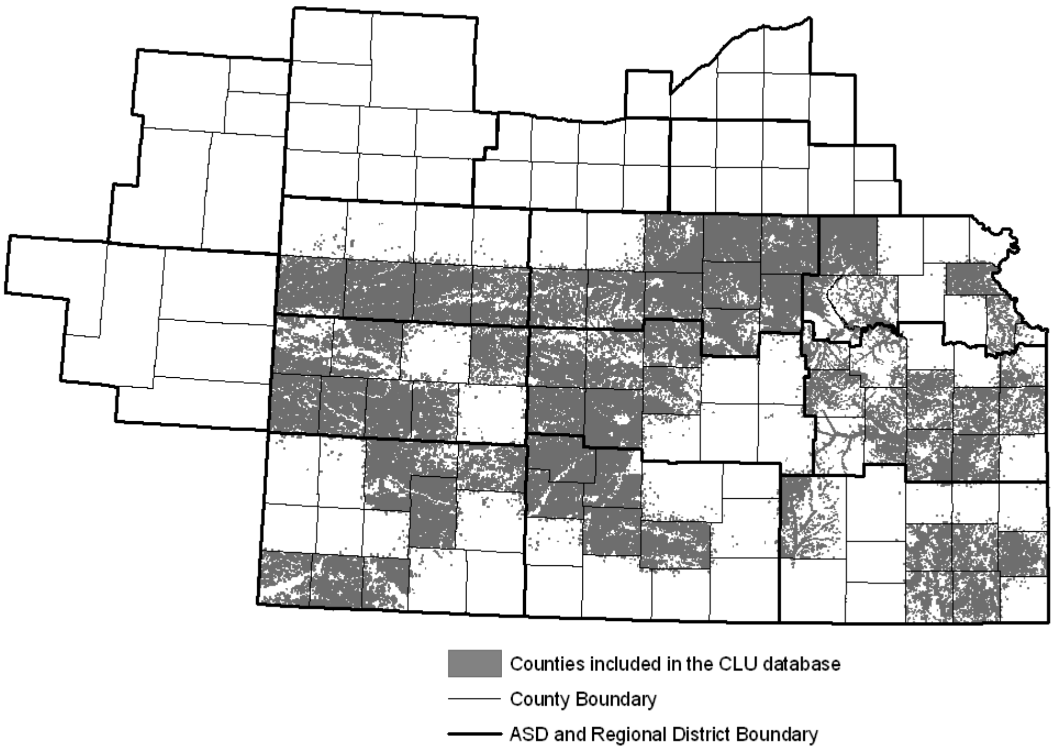

Figure 2.4 Counties included in the CLU database.

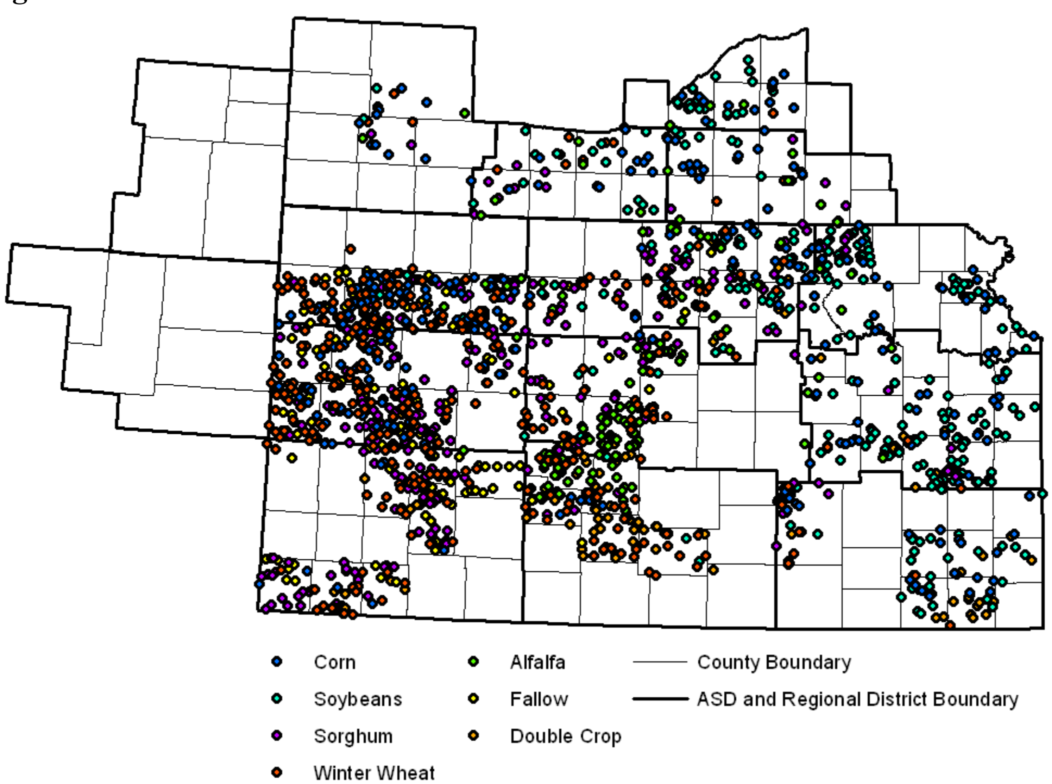

Figure 2.5 CLU Training Sites by crop type.

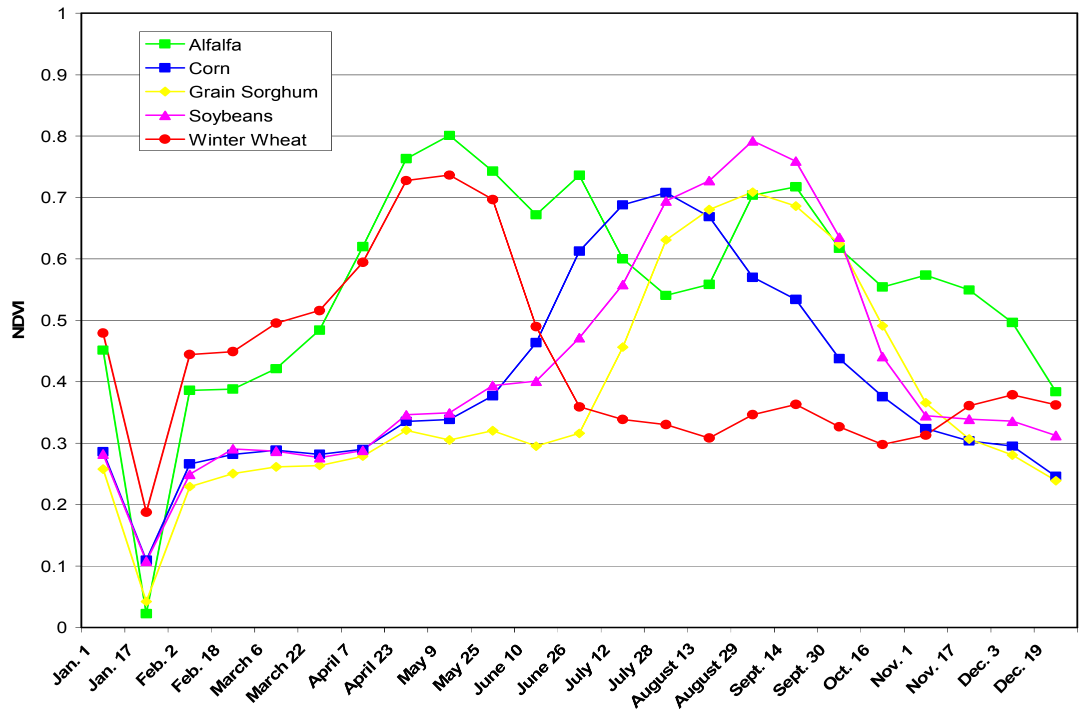

Figure 2.6 Time-series NDVI profiles for Kansas crops.

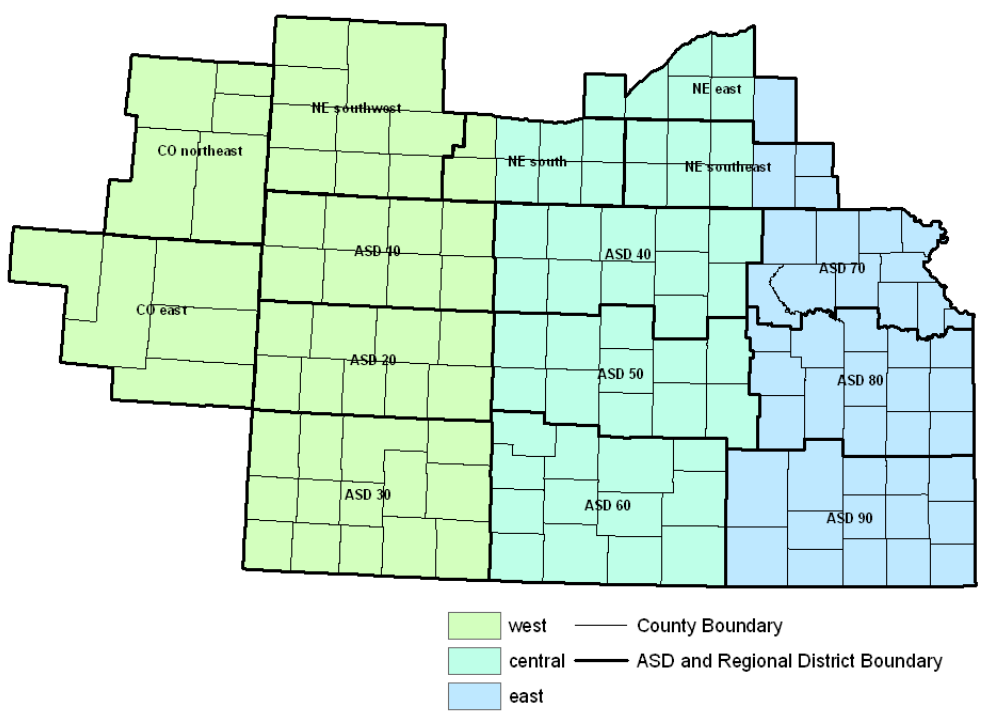

Figure 2.7 Areas by which the classifications were performed. The study area was segmented to coincide with the pronounced east-west precipitation gradient.

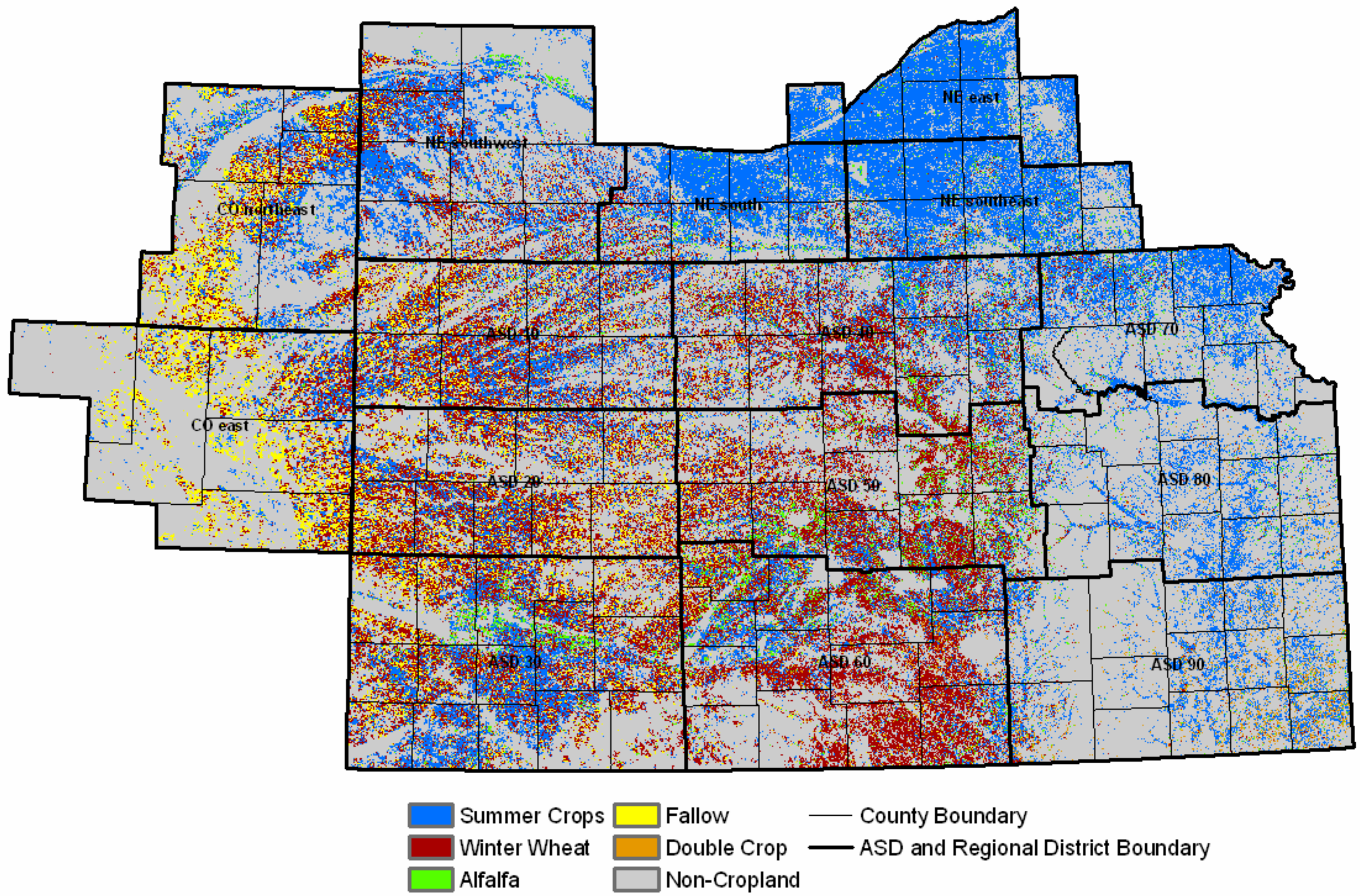

Figure 2.8 2005 general crops map derived from the time-series MODIS NDVI data

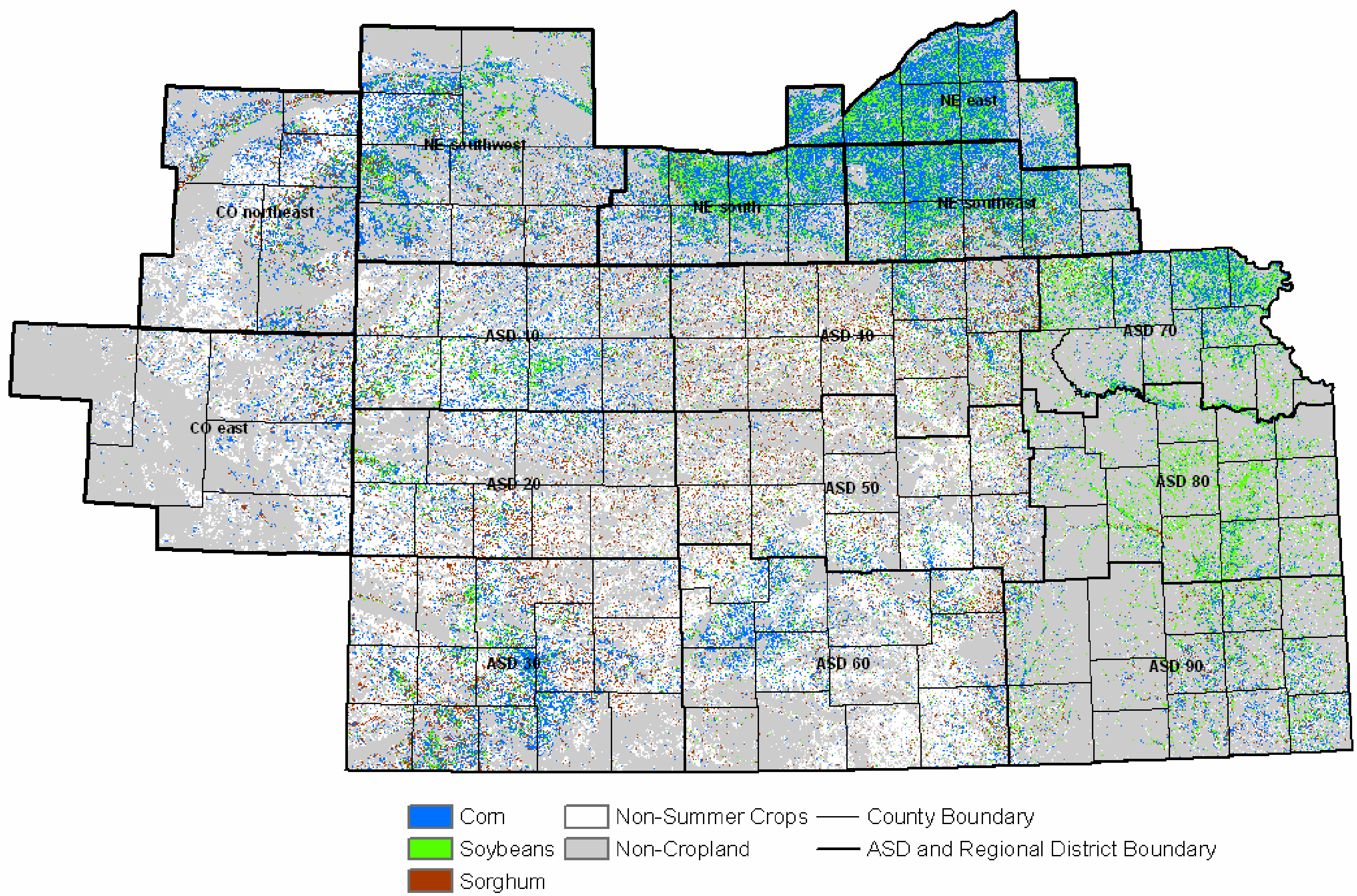

Figure 2.9 2005 summer crops map derived from the time-series MODIS NDVI data.

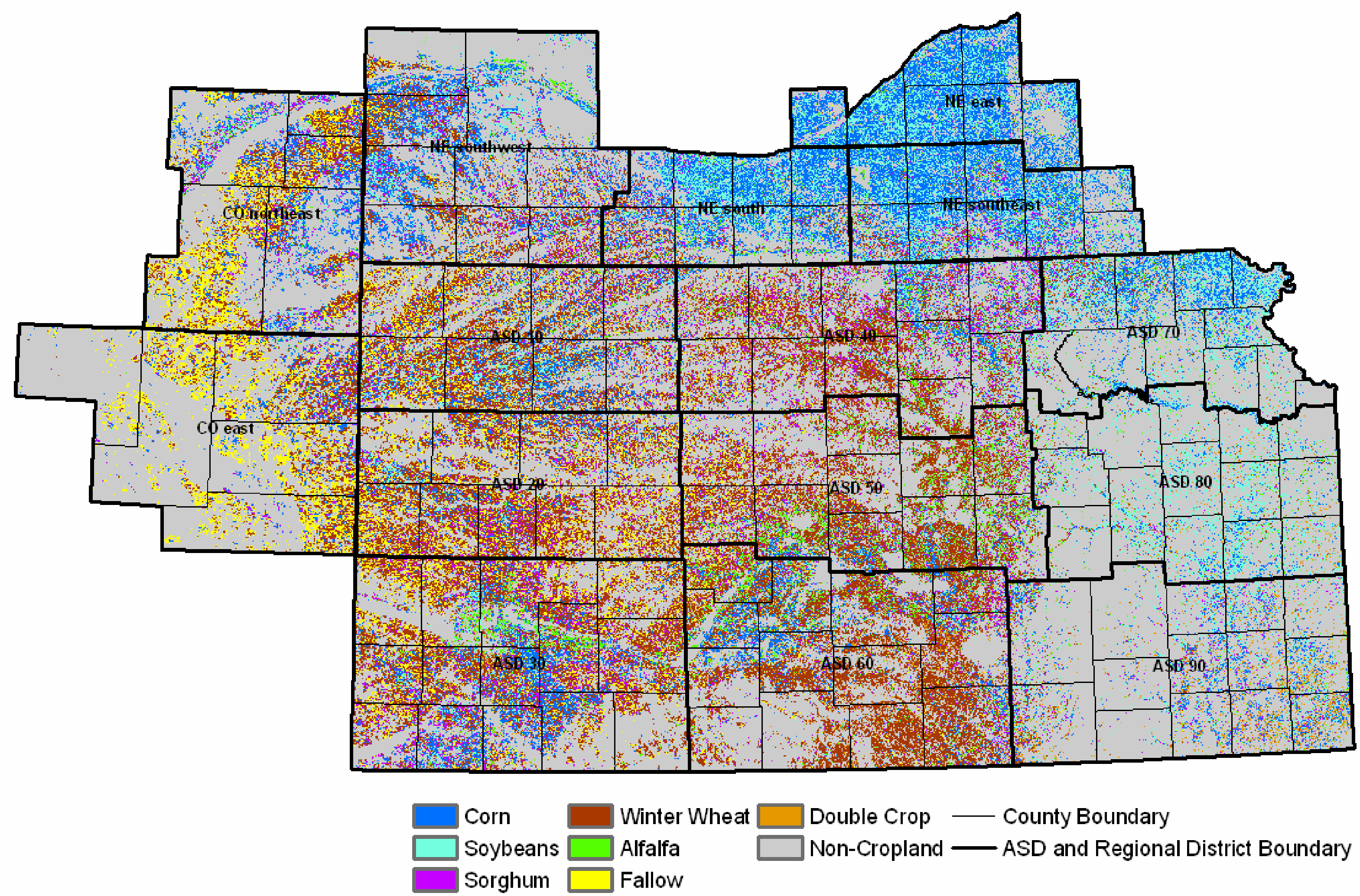

Figure 2.10 2005 map of all crop types derived from the time-series MODIS NDVI data.

Table 2.1 Areal comparisons of the general crops between the MODIS-derived map and the USDA reported statistics for Kansas.

		MODIS Classification		USDA Area		Difference	
		Acres	**% Area**	**Acres**	**% Area**	**Acres**	**% Area**
State	Summer Crops	9,501,892	46.0%	9,300,000	46.2%	201,892	-0.2%
	Winter Wheat	9,803,029	47.5%	10,000,000	49.6%	-196,971	-2.1%
	Alfalfa	1,337,872	6.5%	850,000	4.2%	487,872	2.3%
	Total	20,642,793		20,150,000		492,793	
ASD 10	Summer Crops	1,085,944	45.1%	780,000	38.0%	305,944	7.1%
	Winter Wheat	1,271,745	52.8%	1,235,000	60.0%	36,745	-7.2%
	Alfalfa	50,607	2.1%	42,000	2.0%	8,607	0.1%
	Total	2,408,296		2,057,000		351,296	
ASD 20	Summer Crops	780,969	35.1%	677,000	34.5%	103,969	0.6%
	Winter Wheat	1,428,511	64.2%	1,265,000	64.4%	163,511	-0.2%
	Alfalfa	17,339	0.8%	22,000	1.1%	-4,661	-0.3%
	Total	2,226,819		1,964,000		262,819	
ASD 30	Summer Crops	1,575,797	44.6%	1,382,000	43.5%	193,797	1.1%
	Winter Wheat	1,784,330	50.5%	1,640,000	51.7%	144,330	-1.2%
	Alfalfa	174,475	4.9%	153,000	4.8%	21,475	0.1%
	Total	3,534,602		3,175,000		359,602	
ASD 40	Summer Crops	1,195,135	45.0%	1,047,000	41.5%	148,135	3.5%
	Winter Wheat	1,243,000	46.8%	1,365,000	54.1%	-122,000	-7.3%
	Alfalfa	216,920	8.2%	112,000	4.4%	104,920	3.8%
	Total	2,655,055		2,524,000		131,055	
ASD 50	Summer Crops	724,164	27.1%	835,000	32.5%	-110,836	-5.4%
	Winter Wheat	1,590,182	59.5%	1,550,000	60.4%	40,182	-0.9%
	Alfalfa	356,136	13.3%	183,000	7.1%	173,136	6.2%
	Total	2,670,482		2,568,000		102,482	
ASD 60	Summer Crops	1,012,433	29.4%	1,134,000	31.9%	-121,567	-2.5%
	Winter Wheat	2,173,272	63.2%	2,270,000	63.9%	-96,728	-0.7%
	Alfalfa	252,535	7.3%	151,000	4.2%	101,535	3.1%
	Total	3,438,240		3,555,000		-116,760	
ASD 70	Summer Crops	1,261,909	84.3%	1,209,000	82.8%	52,909	1.5%
	Winter Wheat	124,171	8.3%	195,000	13.4%	-70,829	-5.1%
	Alfalfa	110,009	7.4%	56,000	3.8%	54,009	3.6%
	Total	1,496,089		1,460,000		36,089	
ASD 80	Summer Crops	935,638	84.7%	1,060,000	82.4%	-124,362	2.3%
	Winter Wheat	80,143	7.3%	160,000	12.4%	-79,857	-5.1%
	Alfalfa	89,373	8.1%	67,000	5.2%	22,373	2.9%
	Total	1,105,154		1,287,000		-181,846	
ASD 90	Summer Crops	929,903	83.9%	1,176,000	75.4%	-246,097	8.5%
	Winter Wheat	107,675	9.7%	320,000	20.5%	-212,325	-10.8%
	Alfalfa	70,478	6.4%	64,000	4.1%	6,478	2.3%
	Total	1,108,056		1,560,000		-451,944	

Table 2.2 Areal comparisons of the general crops between the MODIS-derived map and the USDA reported statistics for areas of the Kansas River Basin outside of Kansas.

		MODIS Classification		USDA Area		Difference	
		Acres	**% Area**	**Acres**	**% Area**	**Acres**	**% Area**
CO East	Summer Crops	322,459	29.1%	355,900	28.5%	-33,441	0.6%
	Winter Wheat	777,976	70.2%	860,200	68.9%	-82,224	1.2%
	Alfalfa	8,465	0.8%	31,500	2.5%	-23,035	-1.8%
	Total	1,108,900		1,247,600		-138,700	
CO NE	Summer Crops	673,781	48.3%	502,500	37.2%	171,281	11.1%
	Winter Wheat	687,469	49.3%	772,100	57.2%	-84,631	-7.9%
	Alfalfa	33,650	2.4%	76,200	5.6%	-42,550	-3.2%
	Total	1394900		1,350,800		44,100	
NE SW	Summer Crops	1,463,942	65.8%	1,118,920	63.0%	345,022	2.8%
	Winter Wheat	684,555	30.8%	570,000	32.1%	114,555	-1.3%
	Alfalfa	77,585	3.5%	87,000	4.9%	-9,415	-1.4%
	Total	2,226,082		1,775,920		450,162	
NE South	Summer Crops	1,459,683	84.5%	1,386,000	83.1%	73,683	1.3%
	Winter Wheat	183,810	10.6%	210,000	12.6%	-26,190	-2.0%
	Alfalfa	84,495	4.9%	71,000	4.3%	13,495	0.6%
	Total	1,727,988		1,667,000		60,988	
NE SE	Summer Crops	1,884,516	90.1%	2,085,000	88.4%	-200,484	1.7%
	Winter Wheat	96,612	4.6%	194,500	8.2%	-97,888	-3.6%
	Alfalfa	109,653	5.2%	79,300	3.4%	30,353	1.9%
	Total	2,090,781		2,358,800		-268,019	
NE East	Summer Crops	1,831,364	96.3%	1,798,800	95.9%	32,564	0.3%
	Winter Wheat	13,423	0.7%	20,000	1.1%	-6,577	-0.4%
	Alfalfa	57,688	3.0%	56,300	3.0%	1,388	0.0%
	Total	1,902,475		1,875,100		27,375	

Table 2.3 General crop classification accuracy assessment using the CLU validation data.

		Reference Data					
		Summer Crops	**Winter Wheat**	**Alfalfa**	**Fallow**	**Double Crop**	**Total**
Classified Data	**Summer Crops**	**152**	19	2	5	2	180
	Winter Wheat	16	**159**	2	9	3	189
	Alfalfa	2	4	**20**	0	2	28
	Fallow	4	6	0	**36**	0	46
	Double Crop	2	1	2	0	**14**	19
	Total	176	189	26	50	21	**462**

Overall Accuracy	82.4%
Producer's Accuracy	
Summer Crops	86.3%
Winter Wheat	84.1%
Alfalfa	76.9%
Fallow	72.0%
Double Crop	66.7%
User's Accuracy	
Summer Crops	84.4%
Winter Wheat	84.1%
Alfalfa	71.4%
Fallow	78.3%
Double Crop	73.7%
Kappa	0.69

Table 2.4 Areal comparisons of the summer crop types between the MODIS-derived map and the USDA reported statistics for Kansas.

		MODIS Classification		USDA Area		Difference	
		Acres	% Area	Acres	% Area	Acres	% Area
State	Corn	4,095,236	43.1%	3,650,000	39.2%	445,236	3.9%
	Soybeans	2,904,411	30.6%	2,900,000	31.2%	4,411	-0.6%
	Sorghum	2,502,245	26.3%	2,750,000	29.6%	-247,755	-3.2%
	Total	9,501,892		9,300,000		201,892	
ASD 10	Corn	613,114	56.5%	560,000	71.8%	53,114	-15.3%
	Soybeans	223,618	20.6%	57,000	7.3%	166,618	13.3%
	Sorghum	249,212	22.9%	163,000	20.9%	86,212	2.1%
	Total	1,085,944		780,000		305,944	
ASD 20	Corn	336,449	43.1%	320,000	47.3%	16,449	-4.2%
	Soybeans	121,995	15.6%	18,000	2.7%	103,995	13.0%
	Sorghum	322,525	41.3%	339,000	50.1%	-16,475	-8.8%
	Total	780,969		677,000		103,969	
ASD 30	Corn	772,504	49.0%	800,000	57.9%	-27,496	-8.9%
	Soybeans	244,755	15.5%	100,000	7.2%	144,755	8.3%
	Sorghum	558,538	35.4%	482,000	34.9%	76,538	0.6%
	Total	1,575,797		1,382,000		193,797	
ASD 40	Corn	387,610	32.4%	245,000	23.4%	142,610	9.0%
	Soybeans	278,273	23.3%	319,000	30.5%	-40,727	-7.2%
	Sorghum	529,252	44.3%	483,000	46.1%	46,252	-1.8%
	Total	1,195,135		1,047,000		148,135	
ASD 50	Corn	263,307	36.4%	135,000	16.2%	128,307	20.2%
	Soybeans	149,791	20.7%	210,000	25.1%	-60,209	-4.5%
	Sorghum	311,066	43.0%	490,000	58.7%	-178,934	-15.7%
	Total	724,164		835,000		-110,836	
ASD 60	Corn	547,317	54.1%	390,000	34.4%	157,317	19.7%
	Soybeans	187,159	18.5%	278,000	24.5%	-90,841	-6.0%
	Sorghum	277,957	27.5%	466,000	41.1%	-188,043	-13.6%
	Total	1,012,433		1,134,000		-121,567	
ASD 70	Corn	565,210	44.8%	540,000	44.7%	25,210	0.1%
	Soybeans	642,294	50.9%	593,000	49.0%	49,294	1.8%
	Sorghum	54,405	4.3%	76,000	6.3%	-21,595	-2.0%
	Total	1,261,909		1,209,000		52,909	
ASD 80	Corn	223,209	23.9%	310,000	29.2%	-86,791	-5.4%
	Soybeans	672,964	71.9%	673,000	63.5%	-36	8.4%
	Sorghum	39,465	4.2%	77,000	7.3%	-37,535	-3.0%
	Total	935,638		1,060,000		-124,362	
ASD 90	Corn	386,516	41.6%	350,000	29.8%	36,516	11.8%
	Soybeans	383,562	41.2%	652,000	55.4%	-268,438	-14.2%
	Sorghum	159,825	17.2%	174,000	14.8%	-14,175	2.4%
	Total	929,903		1,176,000		-246,097	

Table 2.5 Areal comparisons for the summer crops between the MODIS-derived map and the USDA reported statistics for areas of the Kansas River Basin outside of Kansas.

		MODIS Classification		USDA Area		Difference	
		Acres	% Area	Acres	% Area	Acres	% Area
CO East	Corn	204,182	63.3%	281,300	79.0%	-77,118	-15.7%
	Soybeans	0	0.0%	0	0.0%	0	0.0%
	Sorghum	118,277	36.7%	74,600	21.0%	43,677	15.7%
	Total	322,459		355,900		-33,441	
CO NE	Corn	446,735	66.3%	499,100	99.3%	-52,365	-33.0%
	Soybeans	0	0.0%	0	0.0%	0	0.0%
	Sorghum	227,046	33.7%	3,400	0.7%	223,646	33.0%
	Total	673,781		502,500		171,281	
NE SW	Corn	907,540	62.0%	920,000	82.3%	-12,460	-20.3%
	Soybeans	310,882	21.2%	110,500	9.9%	200,382	11.4%
	Sorghum	245,520	16.8%	87,500	7.8%	158,020	8.9%
	Total	1,463,942		1,118,000		345,942	
NE South	Corn	886,021	60.7%	910,000	65.7%	-23,979	-5.0%
	Soybeans	478,935	32.8%	424,000	30.6%	54,935	2.2%
	Sorghum	94,727	6.5%	52,000	3.8%	42,727	2.7%
	Total	1,459,683		1,386,000		73,683	
NE SE	Corn	1,141,970	60.6%	1,143,000	54.8%	-1,030	5.8%
	Soybeans	604,939	32.1%	818,000	39.2%	-213,061	-7.1%
	Sorghum	137,607	7.3%	124,000	5.9%	13,607	1.4%
	Total	1,884,516		2,085,000		-200,484	
NE East	Corn	1,194,450	65.2%	1,120,000	62.3%	74,450	3.0%
	Soybeans	606,310	33.1%	658,000	36.6%	-51,690	-3.5%
	Sorghum	30,604	1.7%	20,800	1.2%	9,804	0.5%
	Total	1,831,364		1,798,800		32,564	

Table 2.6 Summer crop classification accuracy assessment using the CLU validation data.

		Reference Data			
		Corn	**Soybeans**	**Sorghum**	**Total**
Classified Data	**Corn**	**139**	10	13	162
	Soybeans	17	**94**	6	117
	Sorghum	19	8	**71**	98
	Total	175	112	90	**377**

Overall Accuracy	80.6%
Producer's Accuracy	
Corn	79.4%
Soybeans	83.9%
Sorghum	78.9%
User's Accuracy	
Corn	85.8%
Soybeans	80.3%
Sorghum	72.4%
Kappa	0.70

Table 2.7 Wardlow's general crop classification accuracy assessment using FSA field site validation data.

		Reference Data				
		Summer Crops	**Winter Wheat**	**Alfalfa**	**Fallow**	**Total**
Classified Data	**Summer Crops**	**180**	1	1	7	188
	Winter Wheat	2	**160**	1	6	168
	Alfalfa	3	5	**18**	0	26
	Fallow	1	1	0	**59**	61
	Total	186	167	20	71	**443**

Overall Accuracy	93.9%
Producer's Accuracy	
Summer Crops	95.6%
Winter Wheat	95.1%
Alfalfa	67.9%
Fallow	96.4%
User's Accuracy	
Summer Crops	96.7%
Winter Wheat	95.6%
Alfalfa	93.2%
Fallow	82.5%
Kappa	0.91

Table 2.8 Wardlow's summer crop classification accuracy assessment using FSA field site validation data.

		Reference Data			
		Corn	Soybeans	Sorghum	Total
Classified Data	**Corn**	**103**	10	10	123
	Soybeans	5	**70**	4	79
	Sorghum	8	5	**51**	64
	Total	116	85	65	**266**

Overall Accuracy	84.0%
Producer's Accuracy	
Corn	88.7%
Soybeans	82.0%
Sorghum	78.2%
User's Accuracy	
Corn	83.5%
Soybeans	88.5%
Sorghum	79.4%
Kappa	0.76

Table 2.9 Comparison between Wardlow's 2001 field sites and the 2005 field sites by crop type.

2001	
Corn	601
Soybeans	442
Sorghum	343
Winter Wheat	430
Alfalfa	243
Fallow	146
Total	**2205**

2005	
Corn	257
Soybeans	225
Sorghum	255
Winter Wheat	312
Alfalfa	124
Fallow	171
Double Crop	98
Total	**1442**

Chapter 3

CROSS-YEAR CLASSIFICATION USING TIME-SERIES MODIS 250-METER VEGETATION INDEX DATA: A PILOT STUDY FOR THE STATE OF KANSAS

3.1 INTRODUCTION

Agricultural landuse/landcover data are among the most important and universally used terrestrial spatial data sets (IGBP, 1990). Up-to-date maps and data sets that map specific crop types are needed over intensively cropped regions, such as the state of Kansas, for applications focused on understanding the role and response of the agricultural sector to environmental change issues (Wardlow et al, 2007). The cropland component of the agricultural landscape is of specific interest because it is intensively managed and has dynamic land cover patterns. Cropland patterns are continually modified by a wide range of human activities like crop rotations and fallowing as well as the introduction of new crops or discontinuation of former crops. As a result, detailed regional-scale cropping patterns need to be mapped on a repetitive basis in order to characterize dynamic land use/land cover patterns and monitor common changes (Wardlow, et al 2007).

Landuse/landcover datasets are only useful if they are sufficiently accurate for the required application. Traditionally, in situ training or sample data from a given year are used for classifying satellite imagery for the same year. However, this can present a problem. In many cases, training sites and sample data are not available on a yearly basis. Many locations might only have complete, quality ground data for a single year over a period of a decade or more. Therefore, it would be beneficial if accurate training data from a single year could be applied to other years.

Landcover Mapping

In the mid to late 1980s, Advanced Very High Resolution Radiometer (AVHRR) derived land cover classifications were produced for Africa (Tucker *et al.*, 1985) and South America (Townshend *et al.*, 1987) using multi-temporal Normalized Difference Vegetation Index (NDVI) data. DeFries and Townshend (1994) generated an 11-class, 1-degree resolution global land cover map from monthly composited NDVI data in support of climate modeling. DeFries *et al.* (1998) improved upon this effort by creating a 13-class global land cover map from the same data set. Loveland *et al.* (1991) derived the first complete land cover map for the conterminous U.S. using 1-km multi-temporal AVHRR NDVI data. In Loveland et al.'s work, seasonal land cover regions (i.e., those that exhibit unique phenological characteristics and represent relatively homogeneous vegetation associations) were classified from a time series of monthly composited NDVI data and other ancillary data sources (e.g., climate and terrain variables). Loveland *et al.* (1999) applied this classification concept globally to produce a similar 1-km global, multidimensional land cover database.

Hansen *et al.* (2000) built upon the previous 8-km work of DeFries *et al.* (1998) and generated a global, 14-class general land cover map using a 12-month time-series of monthly composited 1-km AVHRR data. Currently, an operational global 1-km land cover product is being produced annually from multi-temporal, multi-spectral MODIS data (Friedl *et al.*, 2002). In recent years, the application of MODIS data for landuse/landcover mapping has become widespread (Wardlow and Egbert, 2007; Xiao *et al*., 2006; Xavier *et al*., 2006).

Mapping Kansas Croplands

The study area for this research was Kansas croplands. Brian Wardlow (Wardlow, 2005) and Iwake Masialeti (Masialeti, 2008), in particular, have used MODIS NDVI data to map croplands in the state of Kansas for individual years. For his dissertation research, Wardlow mapped croplands in Kansas for 2001 and has published articles based on this research (Wardlow and Egbert, 2007; Wardlow et al, 2007). Wardlow classified his 2001 cropland data using training site data gathered from USDA Farm Service Agency (FSA) crop photographs. He concluded that croplands in the Great Plains could be accurately mapped using time series MODIS 250m vegetation index data. Masialeti built on Wardlow's work by analyzing NDVI time-series curves for Kansas crops in 2005 for his dissertation research. Masialeti extracted the NDVI signatures from Common Land Unit (CLU) based training data to determine if it was feasible that one training dataset (2005) could be used to classify data from another year (2001). Based on his work Masialeti tentatively concluded that temporal offsets in phenological curves between the years (Figures 3.1 and 3.2) may affect classification accuracies (the offset most likely being the result of climatic variation). Masialeti specifically noted that summer crops would especially be affected by this offset.

MODIS

The datasets that were utilized for this study are derived from Moderate Resolution Imaging Spectroradiometer (MODIS) imagery. The guiding philosophy behind the MODIS design was to collect a daily coverage of well calibrated multi-spectral, multi-resolution imagery from which higher-level quality data sets could be generated to meet the needs of the global change research community. Designed for land, oceanic and atmospheric applications, MODIS adopted a multi-spectral approach by incorporating 36 spectral bands, which cover the visible through long-wave infrared regions. Seven bands were carefully selected to capture the key spectral features of terrestrial targets, and their bandwidths were narrowed to avoid atmospheric absorption regions, particularly for the near infrared band (Justice *et al.*, 1998). MODIS has a radiometric resolution of 12-bits for improved sensitivity to subtle differences in reflectance. MODIS also includes several atmosphere-related bands that measure cloud properties, aerosols, and water vapor, which are used to rigorously correct for atmospheric constituents and enable accurate surface reflectance values to be calculated (Justice *et al.*, 1998).

Spectrally, MODIS contains two 250-m (red and NIR), five 500-m (blue, green, and MIR), and twenty-nine 1km bands. The 250-m bands allow for the detection of many human-induced land cover changes, which were found to occur at or near this spatial scale (Townshend and Justice, 1988). With the 250-m imagery, most individual fields of the Central Great Plains are large enough to be represented by multiple pixels (usually a minimum of 5 pixels). The high temporal resolution (16-day composite period) of the time-series data is also favorable for discriminating crop types based on their unique crop calendars (phenology). MODIS also includes a 250-m Normalized Difference Vegetation Index (NDVI) data set.

NDVI

The cropland datasets for this study were compiled using a time-series of NDVI data. NDVI is a transformation that capitalizes on the differential responses of the visible red (absorbed by chlorophyll pigments) and NIR (reflected by the spongy mesophyll structure of leaves) spectral regions to vegetation and takes the form: NDVI = (NIR – red) / (NIR + red) (Rouse *et al.*, 1974). NDVI is a dimensionless, radiometric measure of green vegetation amount/condition that has been related to several biophysical variables such as biomass, Fraction of Photosynthetically Active Radiation (FPAR), and Leaf Area Index (LAI) (Asrar *et al.*, 1989; Baret *et al.*, 1991). NDVI provides a normalized range of values (-1 to +1) that are directly comparable over both space and time. In order to obtain relatively cloud-free global images, daily observations are composited over a defined time interval (Strahler *et al.*, 1999). A monthly composite period is typically used for global applications, while more localized studies utilize a shorter temporal window (e.g., 10-day or bi-weekly). It is these NDVI composites that have become a standard input for landcover mapping past and present.

3.2 RESEARCH OBJECTIVES

This research was conducted because reference data sets are often difficult and/or expensive to collect and therefore may not be available on an annual basis. With certain dynamic land cover types like cropland, it is often desirable to map these on a yearly basis. The purpose of this part of the research is to determine if a library of standard NDVI time-series curves can be used to classify crop types. Essentially, can one good training dataset be applied to classify multiple years? For the purpose of this study the years 2001 and 2005 were examined. This is due to the fact that good training datasets had already been compiled for those years by Wardlow (for 2001) and Masialeti (for 2005).

The main goal of this study was to determine if training data from 2001 could be used to classify the 2005 data at an acceptable level of accuracy and conversely if training data from 2005 then be used to classify the 2001 data at an acceptable level of accuracy. Some more specific questions this research is intended to address include: (i) How do these accuracies vary spatially and by crop type? (ii) How do the cross-year classification accuracies (2005<>2001) compare to the same-year based classification accuracies (2005<>2005 and 2001<>2001)? (iii) Do the accuracies suggest that this cross-year classification method could be extended spatially and temporally?

3.3 STUDY AREA

The study area for this research is the state of Kansas (Figure 3.3). This study area was chosen because a number of relevant studies have been conducted in Kansas, including biophysical and spectral characteristics of crop-related LULC patterns (Wardlow et al., 2007), crop-specific mapping efforts (Wardlow and Egbert, 2008; USDA-NASS, 2007), and vegetation classification and mapping efforts (Egbert et al., 2001; Lauver et al., 1999; Whistler et al., 1995). The Kansas landscape is dominated by a cropland/rangeland mosaic with 46.9% (10.0 million ha) of its total area intensively cropped (Wardlow, 2005). The state's major crop types include alfalfa (*Medicago sativa*), corn (*Zea mays*), sorghum (*Sorghum bicolor*), soybeans (*Glycine max*), and winter wheat (*Triticum aestivum*). The state's pronounced east-west precipitation gradient strongly influences the specific cropping patterns and associated management practices. On average, western Kansas receives 457-505 mm (18-20 inches) of precipitation per year while eastern Kansas receives 889-1016 mm (35-40 inches) per year (USDA, 2002).

In semi-arid western Kansas, extensive irrigation from groundwater sources (i.e., the Ogallala and Dakota aquifers) and dryland farming techniques (e.g., crop-fallow rotations and no-till farming) maintain high crop production levels despite the area's limited precipitation regime. Approximately 21% (0.9 million ha) of the area's cropland is irrigated and primarily supports alfalfa, corn, and soybeans (USDA, 2002). The remainder of western Kansas is non-irrigated due to inaccessibility of groundwater or financial considerations. Most non-irrigated areas are planted to dryland crops such as sorghum or winter wheat or remain fallow in some years to conserve soil moisture for crop production the next year. The increasing adoption of no-till farming (direct planting of a crop into the crop stubble/residue from the previous year) as a soil moisture conservation technique has resulted in higher yields from traditional dryland crops, increased the acreage of crops with higher water requirements (e.g., corn) in historically non-irrigated areas, and lessened the reliance on crop-fallow rotations (Wardlow, 2005). In eastern Kansas, adequate precipitation is generally received to support high crop production levels without irrigation. Corn and soybeans are the dominant crops in the east, and fallow land use practices are rare. Irrigation is very limited in eastern Kansas and is primarily applied in lowland floodplain areas where groundwater is readily accessible.

On average, Kansas has led the nation in both winter wheat and sorghum area (26.0% and 43.7% of the nation's total, respectively) and production (23.6% and 41.3% of the nation's total, respectively) (NASS, 2004). The economic importance of the state's cropland sector is reflected by its $3.6 billion in crop production in 2004, which ranked sixth nationally (NASS, 2004).

The average parcel size, or "grain", of the landscape also changes from western to eastern Kansas. Western and central Kansas are characterized by a coarse-grained landscape comprised of very large individual fields and large contiguous areas of both cropland and grassland or shrubland areas (Wardlow, 2005). Field sizes commonly range from 65 to 245 ha (160 to 600 acres). In contrast, cropland areas in eastern Kansas are more fragmented and interspersed with other land cover types (e.g., deciduous forest and grassland). Individual fields are also smaller, with most fields being 65 ha (160 acres) or less.

3.4 DATA AND PREPROCESSING

Time-Series MODIS NDVI Data

A 12 month time-series of MODIS 250-meter NDVI data from the years' 2001 and 2005 was used. Three MODIS tiles (h09v05, h10v05, and h10v04) were needed to cover the study area and were compiled by the Kansas Applied Remote Sensing Program. The data were mosaicked by a 16-day composite period and reprojected to the USGS Albers Equal Area projection. The mosaics were then stacked to create 23 time-series periods from January 1 to December 19.

Training Data

The training data utilized in this study come from two sources. Wardlow's (Wardlow, 2005) 2001 training data was derived from United States Department of Agriculture (USDA) Farm Service Agency (FSA) aerial photos. Wardlow used these crop photos to assemble a state- wide field site database of specific crop types. This database consists of 1,240 non-irrigated sites from 51 counties (Figure 3.4).

Masialeti's (Masialeti, 2008) 2005 training data was derived from USDA FSA Common Land Unit (CLU) data. A CLU is the smallest unit of land that has a permanent, contiguous boundary, a common land cover and land management, a common owner and a common producer in agricultural land associated with USDA farm programs (FSA, 2008). CLU boundaries are delineated from relatively permanent features such as fence lines, roads, and/or waterways. CLU data were available for 64 of the 105 Kansas counties.

Masialeti utilized the 2005 Kansas CLU data layer to compile a state-wide field site database of specific crop types, which consists of 1,254 non-irrigated sites from the 64 counties. In addition, training data for fallow landcover had to be extracted from the CLU data layer. Only fields 32 ha (80 acres) or larger were used, this amounts to approximately five 250-m pixels per field site.

Any irregularly shaped fallow fields were removed. It is necessary to remove irregularly shaped fields to assure that at least one entire 250-m MODIS pixel falls within each field's boundary. To remove irregularly shaped fallow fields, a shape index was calculated. This was done by dividing the field's area by the perimeter. Only fields with an index higher than 35 were used. Next, a single 250-m pixel located completely within each field's boundary was selected to represent each site. The NDVI profile associated with the pixel was then extracted from the time-series MODIS data. The extracted NDVI data from the initial field sites for each crop type were subjected to cluster analysis (Romesburg, 2004), using *k-means* clustering, as a way of evaluating variability among field sites within each crop type, and to identify and eliminate outliers. Following Masialeti's protocol, 10 clusters were used. This was completed using the same methodology and protocol as Masialeti. This processing resulted in 1343 final field sites (1173 of Masialeti's plus an additional 171 Fallow) (Figure 3.5).

3.5 METHODS

Classification Overview

The classification process consisted of using NDVI spectral data extracted from the training sites from one year to classify the MODIS image from the other year (i.e., training sites from 2001 to classify 2005, and vice versa). This began by masking out the cropland areas for each year from the MODIS images using the cropland class from the cropland/non-cropland level I maps (Figures 3.6 and 3.7). These cropland areas were then used to perform the classifications.

Decision Tree Classifiers

Decision tree (DT) classifiers are increasingly being used for remote sensing LULC classification problems and currently serve as the main classification algorithm for prominent national- and global-scale LULC mapping efforts such as the USGS NLCD (Homer *et al.*, 2004) and the MODIS Land Cover Type product (MOD12Q1) (Friedl *et al.*, 2002). DTs are non-parametric, hierarchical classifiers that predict class membership by recursively partitioning data sets into more homogeneous, mutually exclusive subsets via a series of internal nodes (Wardlow, 2007). At each internal node, all possible thresholds of all independent variables are examined and the specific threshold of a single variable is selected. The variable that is selected will be the one that results in the most homogeneous subset based on statistical deviance (Wardlow, 2007). This is then selected to separate the data into two exclusive subsets. This procedure is repeated to produce more homogeneous subsets and continues until a tree is created where each node contains training observations from a single class. Once the DT's classification structure is established, each observation (pixel) from the unseen image data is passed through the tree and assigned to the class of the leaf node into which it falls (Wardlow, 2007).

DTs offer several advantages over traditional supervised classifiers. Since DTs are 'non-parametric' there are no assumptions regarding the distributions of the input data. In addition, they recognize a variety of data types (categorical, hierarchical, numeric) and are well suited for dealing with noise or gaps in the data. DTs also have several additional features incorporated to improve classification accuracies over traditional supervised classifiers.

'Pruning' is a key feature that has typically been incorporated into the DT classification process for LULC mapping applications in order to make the tree's predictive ability more robust when applied to unseen data (Hansen *et al.*, 1996; Friedl and Brodley, 1997; DeFries and Cheung-Wai Chan, 2000, Friedl *et al.*, 2002; Homer *et al.*, 2004). Pruning involves removing parts of the tree (i.e., internal nodes) that are predicted to have a relatively high error rate or contribute little to reducing the deviance in the training data.

‘Boosting’ is an ensemble classification technique developed in the machine learning community (Shapire 1990) that has recently been incorporated with DT classifiers for LULC classification (Friedl *et al.*, 1999; DeFries and Chan, 2000). The purpose of boosting is to generate several classifiers (i.e., decision trees) rather than a single classifier to improve the accuracy of the base classification algorithm. Boosting estimates multiple classifiers from a base classification algorithm in an iterative fashion while systematically varying the training sample through reweighting or a resampling procedure. The final ‘boosted’ classification output is produced by a weighted voting scheme across the multiple classifiers. Any number of iterations can be performed, but previous work using both non-remote sensing (Freund and Schapire, 1996) and remote sensing data (Friedl *et al.*, 1999) has shown that improvements in classification accuracy are minimal after 7 to 10 iterations. For most previous LULC mapping efforts that have applied boosting (Friedl *et al.*, 1999; DeFries and Chan, 2000; McIver and Friedl, 2001), 10 iterations were used.

The commercial decision tree classifier See5 was used to perform the classifications. This univariate classifier was chosen because it has widely been used to classify landcover over large areas. See5 is the standard in the industry and was also the classifier used by Wardlow (2007). For this study, a pruning factor of 25% was used along with the boosting option set to 10 iterations. These are the same See5 parameters that Wardlow concluded produced the best overall results (Wardlow 2007).

3.6 RESULTS AND DISCUSSION

The results for the classification using the 2001 satellite imagery and 2005 training data are discussed first. This is followed by a discussion of the results for the classification using the 2005 satellite imagery and the 2001 training data. The results are outlined using three types of assessment: visual, areal, and statistical. Since there is little variation between the cross-year maps visually, these assessments are outlined in one section.

Visual Assessment – Both Cross-Classifications (2001<>2005 and 2005<>2001)

General Crop Maps

Both of the classified general crop maps (2001<>2005, Figure 3.8, and 2005<>2001, Figure 3.11) were consistent with the state's reported cropping patterns. With the general crop map, the summer crop class is dominant in the east. The high concentration of summer crops in the northeast corner of ASD 70 marks the southern extent of the Corn Belt. Winter wheat is the dominant crop throughout the central part of the state which is part of the Winter Wheat Belt. The maps also display concentrations of winter wheat in some areas of the western ASDs known for their wheat production. Summer crops can clearly be seen along the Republican River valley (ASD 40) and the Kansas River valley, which traverses the border between ASDs 70 and 80. High concentrations of summer crops also can be seen in ASD 30 in the southwest and the northwestern part of ASD 60. These summer crops are grown using center-pivot irrigation practices that are common to the region. High concentrations of alfalfa are evident in ASDs 30, 50 and 60. Note also the high concentration of fallow land in the western ASDs. This is consistent with the cropping practices used in more arid regions like western Kansas. On a yearly basis, as much as 30% of the cropland in this area lies fallow.

Summer Crop Maps

With the summer crop maps (Figures 3.9 and 3.12), corn and soybeans are the dominant crops in eastern Kansas. High concentrations of corn and soybeans were mapped along the Republican River in ASD 40 and the Kansas River along the border between ASDs 70 and 80. A large concentration of corn was also mapped in the irrigated cropland in northwestern ASD 60. Large areas of irrigated corn and soybeans were also mapped in ASD 30. The maps also clearly show the transition to more sorghum on the non-irrigated cropland in the western part of the state. This would be consistent with the drought tolerance of sorghum. In particular, the higher concentrations of sorghum were mapped in ASDs 20, 30 and 40. This is consistent with the state cropping patterns. However, it appears that ASDs 10, 50, and 60 should have higher concentrations of sorghum than were mapped.

2001 General Classification Using 2005 Training Data

Areal Comparison

With the general crop classification, state-level areal comparisons (Table 3.1) found that the general crop map showed moderately strong similarities with the USDA reported areal statistics. Wheat was the dominant crop followed by summer crops and alfalfa. The USDA statistics suggest that wheat and summer crops should be essentially equal in area. It is also important to note that alfalfa was over-classified by a ratio of two to one. Wheat was over-classified in all nine ASDs, although it was very close to the USDA reported acreage in ASD 90.

ASD-level comparisons found a moderate overall correlation (r) of 0.71 between the map and the USDA reported general crop acreages. Wheat had the highest correlation (r=0.98) followed by alfalfa (r=0.89) and summer crops (r=0.68). Note that based on Masialeti's research, he predicted that climatic variations between the years resulted in variations in green-up dates and the overall phenology. This was especially the case with the summer crops. Masialeti noted that summer crops would likely have lower classification accuracies compared to other types. In Kansas, summer crops are planted at relatively different times. Corn is typically the earliest planted summer crop (April to mid-May) followed by soybeans (mid-May to mid-June) and sorghum (late-May to late-June) (Shroyer *et al.*, 1996).

Summer crops were under-classified across the entire state. Some moderate under-classification of summer crops occured in the western (-10.4%) and central (-12.8%) part of the state with major under-classifications in the east

(ASDs 70 (-20.7%), 80 (-28.5%) and 90 (-25.5)). The map displays some moderate over-classification of wheat in the west (+9.7% to +10.4%) along with major over-classifications in the east (+17.0% to +30.0%). Alfalfa was moderately over-classified in the central part of the state (+5.7% to +8.6%). A high level of agreement (+0.5%) between the classified map and reported acreage for alfalfa occurred in the northeast (ASD 70). A moderate over-classification of alfalfa (+8.5%) occurred in the southeast (ASD 90). Based on a visual assessment of the NDVI time-series data it appears that fields that are being mapped as alfalfa in ASD 90 are actually fields that are double cropped. Double cropping is common in the southeastern part of the state where winter wheat is followed by a subsequent summer crop (usually soybeans). The double peak of the double-cropping NDVI pattern somewhat mimics the growth and cut cycle of alfalfa.

Statistical Accuracy Assessment

The general crop map had a moderate overall accuracy of 70.3% (Table 3.2). The class-specific user's and producer's accuracies ranged from 84.8% (alfalfa) to 56.8% (summer crops). Based on the error matrix, the following misclassifications were observed: (1) summer crops were frequently classified as winter wheat, (2) winter wheat was frequently classified as summer crops and fallow, (3) alfalfa was occasionally classified as winter wheat and summer crops, and (4) fallow was frequently classified as wheat.

The NDVI curves for summer crops and winter wheat are vastly different. They are nearly the reverse of one another (Figure 3.1). Therefore, these misclassifications are likely due to an error in the training sites where either summer crop sites were actually winter wheat sites or winter wheat sites where actually summer crops were grown . It is likely that alfalfa was occasionally classified as winter wheat because they share nearly identical NDVI values during the early part of the growing season (March thru June) (Figure 3.1). Alfalfa was also sometimes classified as summer crops. Alfalfa and summer crops have dissimilar NDVI response curves. As a result, there is a possibility that some of the alfalfa training sites were actually summer crop training sites. A potential reason why fallow was frequently classified as winter wheat is due to the presence of weeds growing on the fallow land. This would lead to NDVI values more similar to those of winter wheat thus causing some confusion.

2001 Summer Classification Using 2005 Training Data

Areal Comparison

With the summer crop classification, a moderate level of agreement was found between the map and the USDA summer crop areas at the state level (Table 3.3). With the classified map, corn was the dominant crop followed by soybeans and sorghum. According to the USDA statistics, sorghum was the dominant crop, followed by corn and soybeans. Based on the USDA areal statistics, all three summer crops were under-classified at the state level. The biggest areal difference was with sorghum, where not even half of the USDA reported acreage was classified on the map.

ASD-level comparisons found overall correlation (r) of 0.65 between the map and the USDA reported summer crops acreage. Corn had the highest correlation (r=0.92) followed by sorghum (r=0.69) and soybeans (r=0.35). A major under-classification of corn (-17.2%) occurred in ASD 10. Major over-classification of corn occurred in ASDs 50 (+21.3%), 60 (+22.2%), and 90 (+38.3%). There was a major discrepancy with soybeans across the state. In general, this discrepancy is characterized by over-classifications in western Kansas and moderate to major under-classifications in central and eastern Kansas. Major over-classifications of soybeans (+17.7% to +23.6%) exist in the west (ASDs 10, 20, and 30). Major under-classifications of soybeans exist in ASDs 80 (-23.0%) and 90 (-31.8%).

Sorghum was under-classified across most of the state (except ASDs 70 and 80). Of these, ASDs 20, 30, 40, 50, and 60 had the greatest variation due to major under-classifications (-17.0% to -33.2%).

Statistical Accuracy Assessment

The summer crop map had a moderate overall accuracy of 73.0% (Table 3.4). The class-specific user's and producer's accuracies ranged from 76.9% (soybeans) to 64.2% (sorghum). Based on the error matrix, the following misclassifications were observed: (1) corn was often classified as soybeans and sorghum, (2) soybeans were often classified as corn, and (3) sorghum was frequently classified as corn.

It is likely that corn was often classified as sorghum and soybeans because their NDVI curves are almost identical during the early stages of the growing season (April thru June) (Figure 3.1). There was also some confusion where soybeans were classified as corn. Again, this is likely due to the very similar NDVI values they share early in the growing season. There was significant confusion between sorghum and corn where sorghum was frequently classified as corn. Some of this can be explained by the closely matching NDVI values early in the growing season. However, their values during the peak of the growing season (July thru September) are significantly different. This leads to the assumption that some of the sorghum training sites might have actually been located on corn fields.

Comparison to Wardlow's 2001 Classifications

The level of accuracy achieved using this cross-year classification (2001 satellite data using 2005 training data) was not nearly as accurate as Wardlow's 2001 classifications. Wardlow's 2001 classifications had accuracies generally greater than 84% (98.7% for the general crop map and 84% for the summer crop map) while the cross-year classification had an overall accuracy of 70.3% for the general map and 73.0% for the summer map.

First, comparisons between the general crop maps were evaluated. The most notable difference between Wardlow's classification and the cross-year classification is with winter wheat. With Wardlow's 2001 map, winter wheat was slightly under-classified, while with the cross-year map, winter wheat was moderately over-classified. Variation also exists between the two classifications in regard to the summer crops. Wardlow's 2001 map slightly over-classified summer crops while summer crops were moderately under-classified with the cross-year map (the latter mainly due to summer crops being misclassified as winter wheat). One similarity that stands out between both maps is the over-classification of alfalfa in southeast Kansas (ASD 90). Visual inspection of the time-series data suggests that most of the areas mapped as alfalfa in this region are actually fields that are double cropped, where winter wheat is followed by a subsequent summer crop (predominantly soybeans).

Secondly, comparisons between the two summer crop maps were evaluated. Based on visual and areal assessments these maps are fairly similar. With both Wardlow's 2001 map and the cross-year map soybeans were moderately over-classified in the west (ASDs 10, 20, and 30) and moderately under-classified in the east (ASDs 70, 80, and 90). The areas mapped as corn were quite comparable between the two maps for most ASDs. The main difference between the two maps was the areas mapped as sorghum. With Wardlow's 2001 map the areas mapped as sorghum were comparable to what the USDA had reported. However, with the cross-year map, sorghum was significantly under-classified across most of the state (except ASDs 70 and 80). It is this significant under-classification of sorghum and the significant over-classification of winter wheat that contributed most to the lower overall accuracy of the cross-year classification.

2005 General Crop Classification Using 2001 Training Data

Areal Comparison

At the state level, the classified areas of the general crop map were found to be consistent with the USDA reported areal statistics (Table 3.5). Summer crops and winter wheat were the dominant crops constituting essentially equal areas (roughly 10 million acres each). These were followed by alfalfa, then fallow. It is important to note that according to the USDA areal statistics, alfalfa was over-classified in the map by a margin of more than two to one.

ASD-level comparisons found a fairly high overall correlation (r) of 0.79 between the map and the USDA reported general crop acreage. Wheat had the highest correlation (r=0.96) followed by summer crops (r=0.77) and alfalfa (r=0.72). Still, wheat was moderately under-classified (-6.0% to -6.8%), mainly in the east (ASDs 70, 80, and 90). A moderate to major under-classification of wheat (-11.6%) also occurred in ASD 40. Some discrepancy also exists with the summer crops across the state. Summer crops were moderately under-classified in ASDs 50 (-9.6%), 60 (-8.3%), and 80 (-7.8%). A major under-classification of summer crops (-20.6%) occurred in ASD 90. Alfalfa was over-classified in all nine districts with major over-classifications in the central (+10.2% to +11.9%) and eastern (+10.7% to +26.6%) parts of the state. Yet there was a high level of agreement for alfalfa (+0.2%) in ASD 20. Alfalfa was greatly over-classified in ASD 90 where the classified map contained seven times more alfalfa (449,254 acres) than the reported USDA figures (64,000)

(USDA, 2006). Based on Wardlow's findings, some of the areas classified as alfalfa in this district are not alfalfa at all. Instead, these are areas that are double cropped with winter wheat and a subsequent summer crop (usually soybeans).

Statistical Accuracy Assessment

The general crop map had a moderate overall accuracy of 74.1% (Table 3.6). The class-specific accuracies ranged from 80.7% (winter wheat) to 56.9% (fallow). Based on the error matrix, the following misclassifications were observed: (1) summer crops were occasionally classified as winter wheat. (2) winter wheat was occasionally classified as summer crops and fallow, (3) alfalfa was frequently classified as winter wheat, and (4) fallow was frequently classified as winter wheat.

The NDVI curves for summer crops and winter wheat are vastly different. As noted before, they are nearly the reverse of one another (Figure 3.1). Therefore, these occasional misclassifications are likely due to an error in the training sites where either summer crop sites were actually winter wheat sites or winter wheat sites were actually fields where summer crops were grown. In addition, winter wheat was sometimes classified as fallow. This may be due to the fact that winter wheat and fallow share very similar NDVI profiles after winter wheat is harvested (from mid-June thru October). It is likely that alfalfa was frequently classified as winter wheat because they share nearly identical NDVI values during the early part of the growing season (March thru June) (Figure 3.1). A potential reason why fallow was frequently classified as winter wheat is due to the presence of weeds growing on the fallow land.

This would lead to NDVI values more similar to those of winter wheat thus causing some confusion.

2005 Summer Crop Classification Using 2001 Training Data

Areal Assessment

Statewide, a moderate level of agreement was found between the classified map and USDA areal statistics (Table 3.7). In both the USDA statistics and the map, corn was the dominant summer crop followed by soybeans and sorghum.

ASD-level comparisons found a fairly high overall correlation (r) of 0.75 between the map and the USDA reported summer crops acreage. Soybeans had the highest correlation (r=0.90) followed by corn (r=0.85) and sorghum (r=0.50). The low correlation for sorghum is due to its major under-classification (-18.4% to -34.8%) in central Kansas (ASDs 40, 50, and 60). Sorghum was also moderately under-classified (-10.0%) in ASD 20. There was a very high level of agreement (+0.6%) between the map and USDA statistics for sorghum in ASD 70 and a high level of agreement (+1.3%) in ASD 80. The map depicts a moderate under-classification of corn in ASD 10 (-14.0%) in the west and ASDs 70 (-10.3%) and 80 (-8.1%) in the east. Major over-classifications of corn occurred in the central part of the state in ASDs 50 (+33.6%) and 60 (+26.8%). A moderate to major over-classification of soybeans (+10.0% to +13.1%) occurred in the western ASDs (10, 20, and 30). In addition, soybeans were also moderately over-classified (+9.7%) in ASD 70.

Statistical Accuracy Assessment

The summer crop map had a moderate overall accuracy of 75.1% (Table 3.8). The class-specific accuracies ranged from 81.3% (soybeans) to 63.2% (sorghum). Based on the error matrix, the following misclassifications were observed: (1) corn was occasionally classified as sorghum and soybeans, (2) soybeans were occasionally classified as corn, and (3) sorghum was frequently classified as corn.

It is likely that corn was sometimes classified as sorghum and soybeans because their NDVI curves are almost identical during the early stages of the growing season (April thru June) (Figure 3.1). There was also some confusion where soybeans were classified as corn. Again, this is likely due to the very similar NDVI values they share early in the growing season. There was significant confusion between sorghum and corn where sorghum was frequently classified as corn. Some of this can be explained by the closely matching NDVI values early in the growing season. However, their values during the peak of the growing season (July thru September) are significantly different. This leads to the assumption that some of the sorghum training sites might have actually been located on corn grown fields.

Comparison to the 2005 Classifications

When comparing the cross-year classification (2005 satellite data using 2001 training data) to the 2005 classification the most notable difference is the lower accuracy of the cross-year classification. The 2005 classification had an overall accuracy of 82.4% for the general map and 80.6% for the summer crops map while the overall classification accuracy for the cross-year classification was 74.1% for the general map and 75.1% for the summer map.

The greatest discrepancy between the two maps exists with alfalfa. With the 2005 classified map, alfalfa was slightly to moderately over-classified throughout central and eastern portions of the state. This was the same case with the cross-year map but with moderate to major over-classifications, especially in the southeast (ASD 90). Other major variations between the maps involve the winter wheat cover type. With the cross-year classified map, major under-classifications of winter wheat occurred in ASD 40 as well as the eastern part of the state (ASDs 70, 80, and 90). The cross-year classified map also displays some moderate to major under-classifications of the summer crop class when compared to the 2005 classified map. This is particularly the case in the central (ASDs 40, 50, and 60) and eastern (ASDs 80 and 90) parts of the state.

Comparisons between the summer crop maps also were evaluated. Based on visual and areal comparisons both maps display the same general patterns. The main difference is the level of over or under classification. Both maps display a moderate over-classification of soybeans in the west (ASDs 10, 20, and 30). Surprisingly, these over-classifications were less severe with the cross-year classified map. With both maps, sorghum was moderately under-classified throughout the central part of the state (ASDs 40, 50, and 60). However, with the cross-year classified map, there was a very high level of agreement for sorghum in ASDs 70 and 80. These results are even better than those achieved for sorghum in this region with the 2005 classified map. The results for the corn cover type match up well between the two maps. For corn, both maps have a fairly high level of accuracy for corn with moderate over-classifications in the central part of the state (ASDs 40, 50, and 60). It is likely that the significant over-classification of alfalfa and under-classification of winter wheat provided the greatest contribution to the lower overall accuracy of the cross-year classified map.

3.7 CONCLUSTIONS

The results of this study demonstrated that applying a library of MODIS 250-m NDVI spectral response curves to other years is viable for regional scale crop mapping, yet with lower than desired levels of accuracy. The LULC cross-year crop maps had relatively low overall classification accuracies (70.3% & 73.0% for the 2001 general and summer maps respectively and 74.1% & 75.1% for the 2005 general and summer maps respectively) when compared to the standard (85%+) for land cover mapping from satellite imagery. Yet the general crop patterns were consistent with the known cropping practices in the region. It is likely that the diverse environmental conditions, variation in cropping practices, and plant health between the years had a significant influence on the classification results. These results seem to support Masialeti's conclusion that time series NDVI response curves for crops over a growing period for one year of valid ground reference data may not be useful for mapping crops for a different year without taking into account temporal shifts in the NDVI values due to inter-annual climate variations or changes in agricultural management practices.

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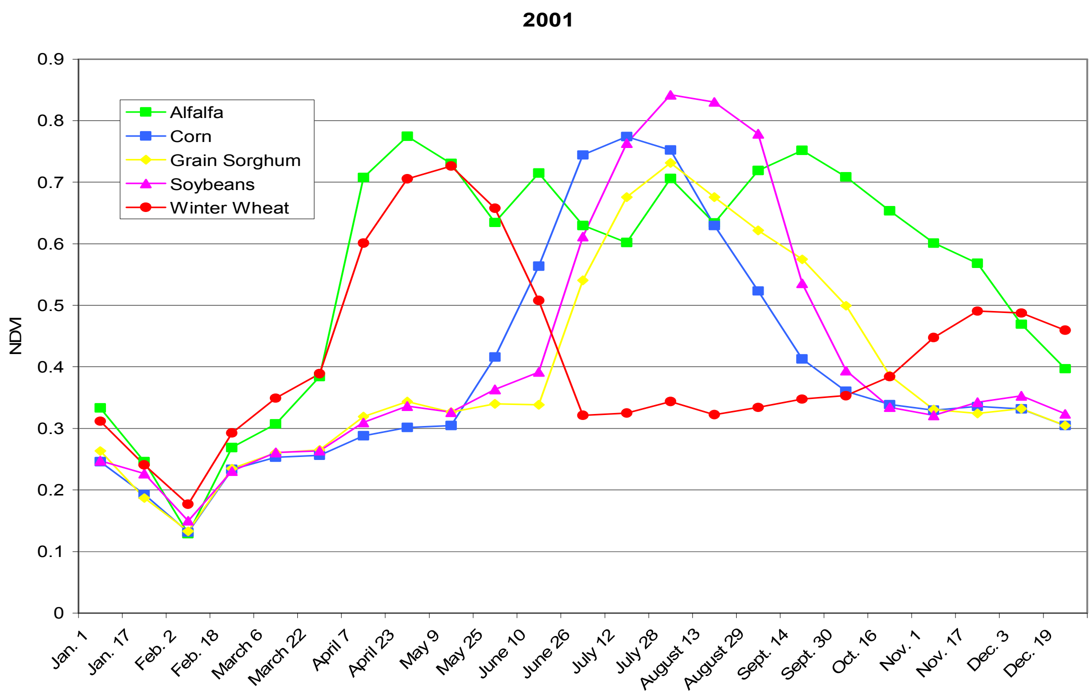

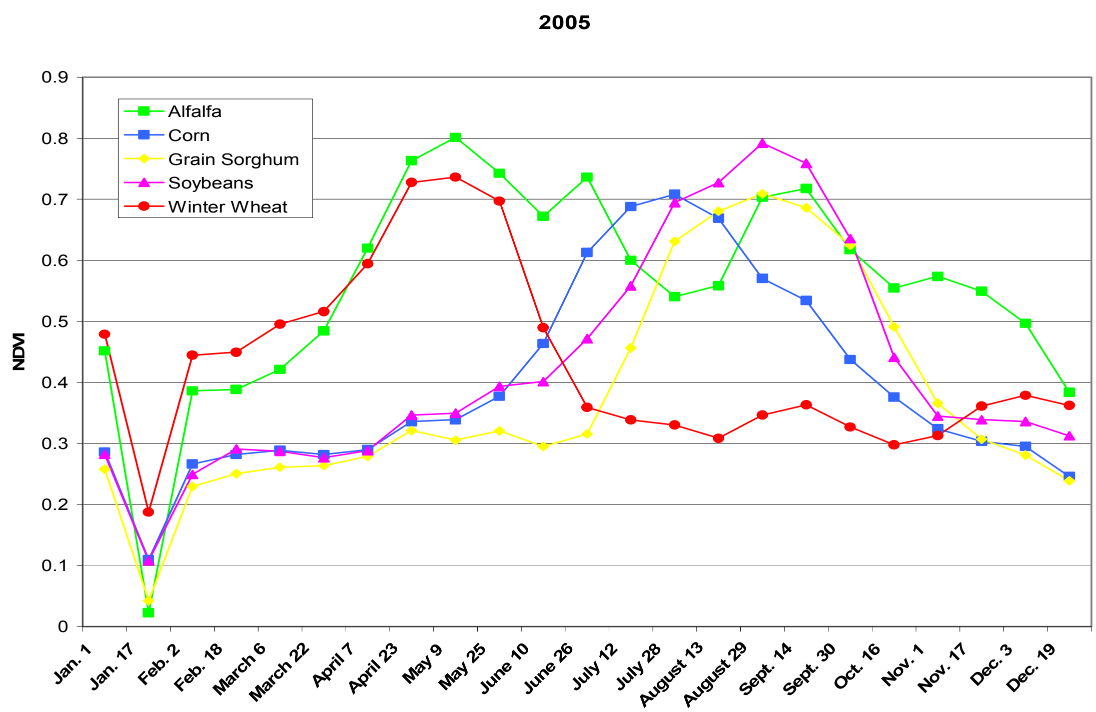

Figure 3.1 2001 and 2005 NDVI curves for Kansas crops.

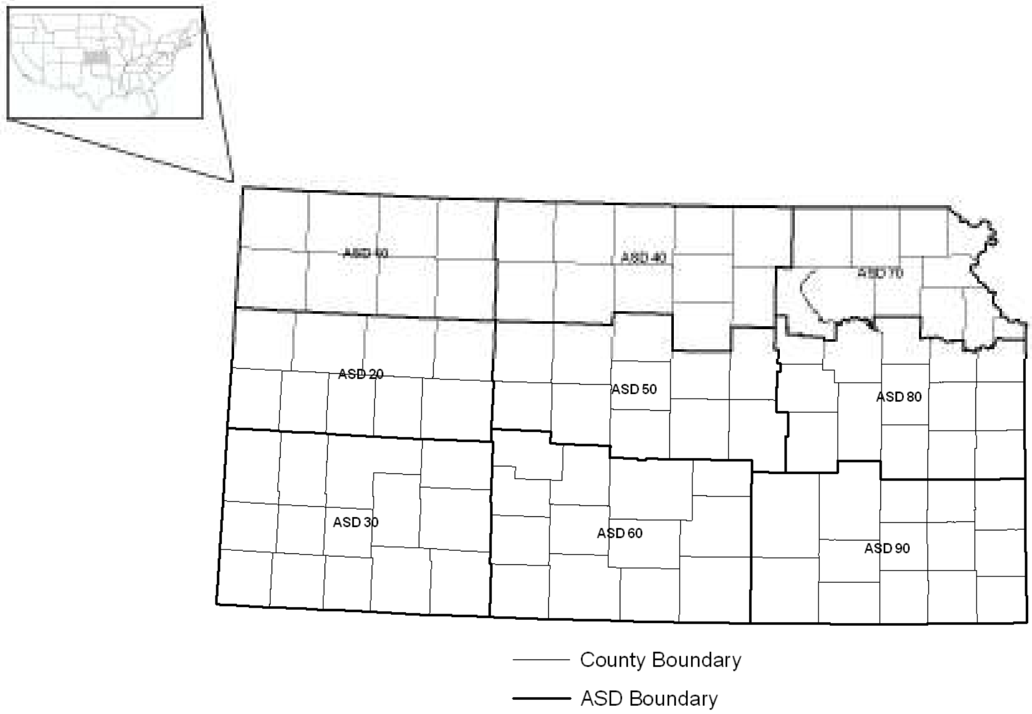

Figure 3.2 The Kansas study area with ASD and County boundaries.

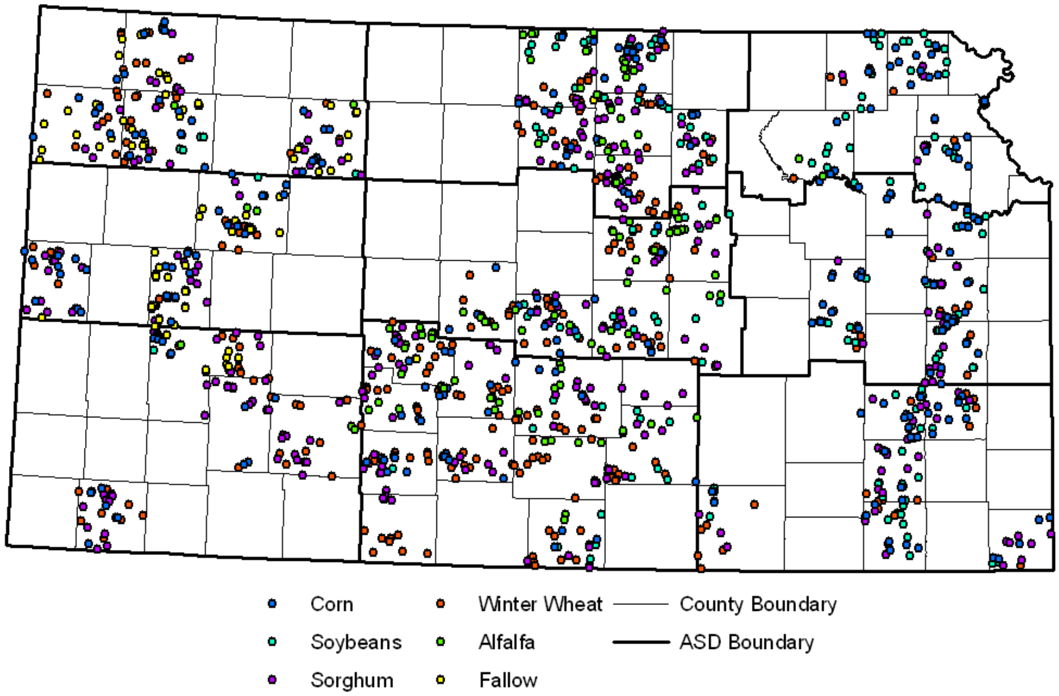

Figure 3.3 Wardlow's 2001 training sites by crop type (Wardlow, 2005).

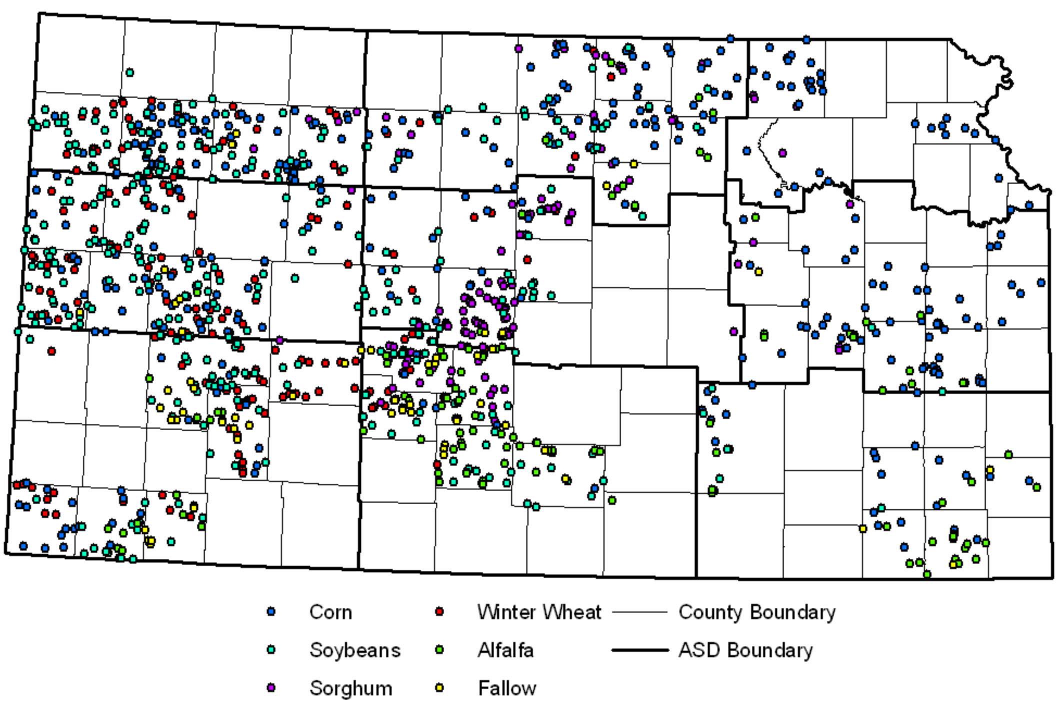

Figure 3.4 Masialeti's 2005 training sites by crop type (Masialeti, 2008).

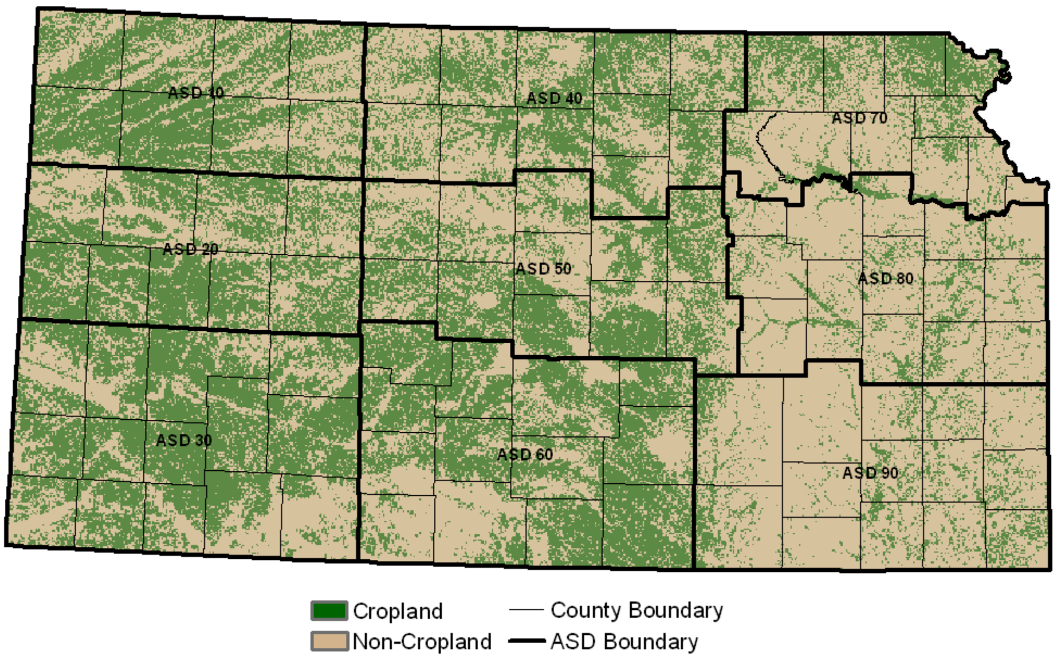

Figure 3.5 Wardlow's 2001 Cropland/Non-Cropland Map (Wardlow, 2005).

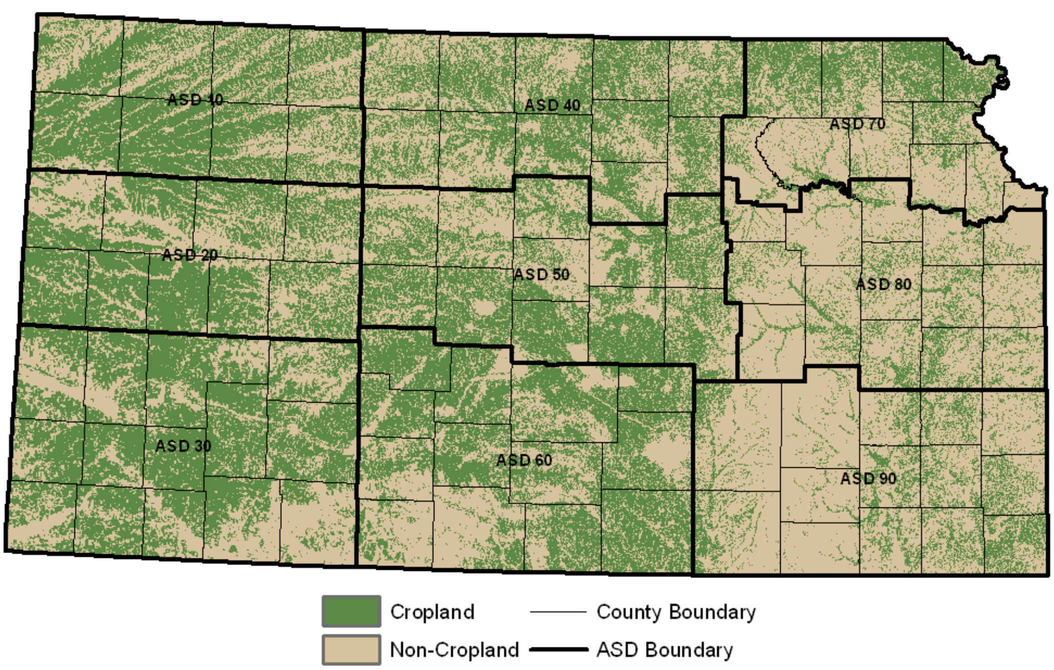

Figure 3.6 2005 Cropland/Non-Cropland Map

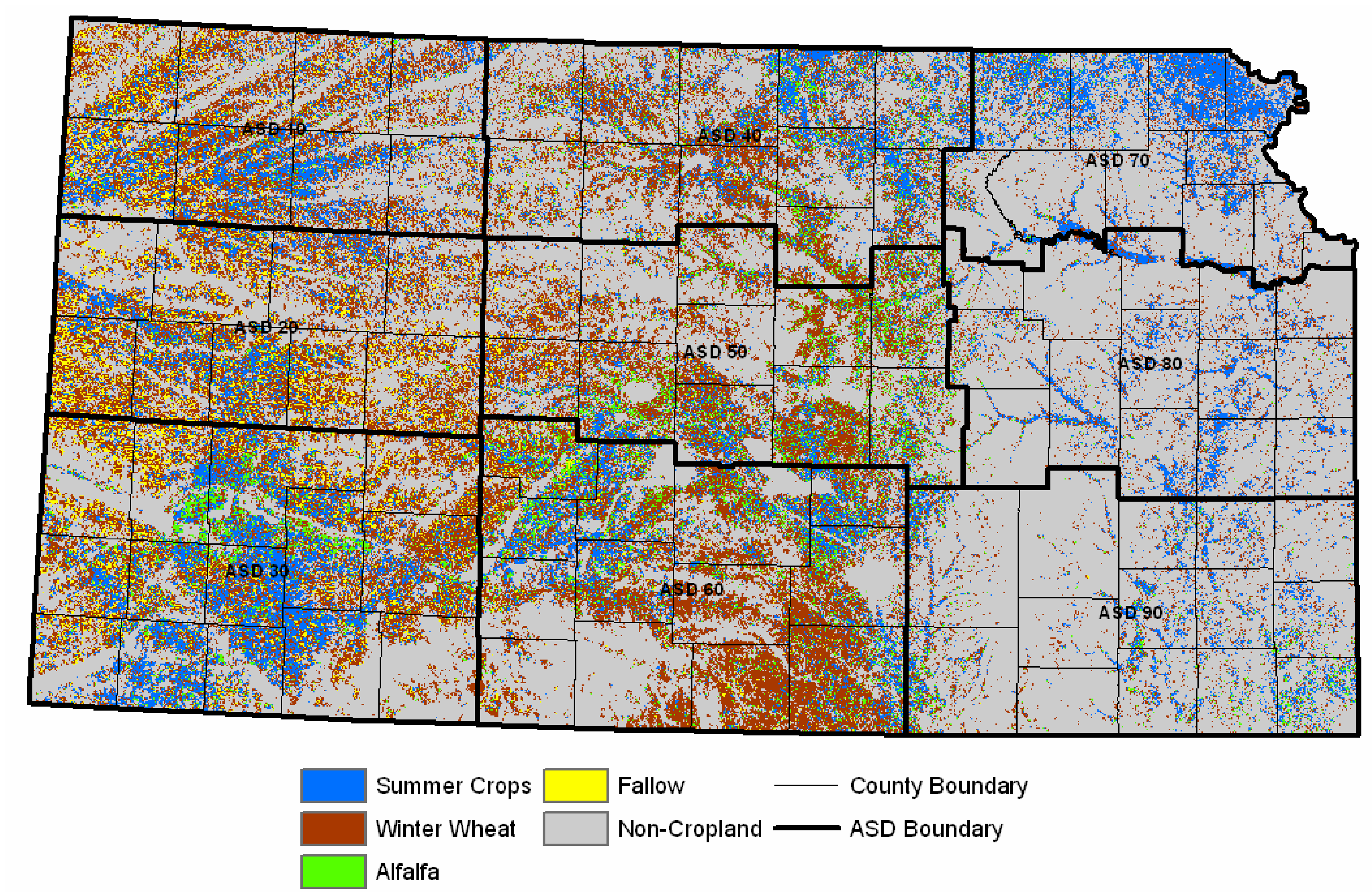

Figure 3.7 2001 general crops map derived from the 2005 training data and 2001 time-series MODIS NDVI data.

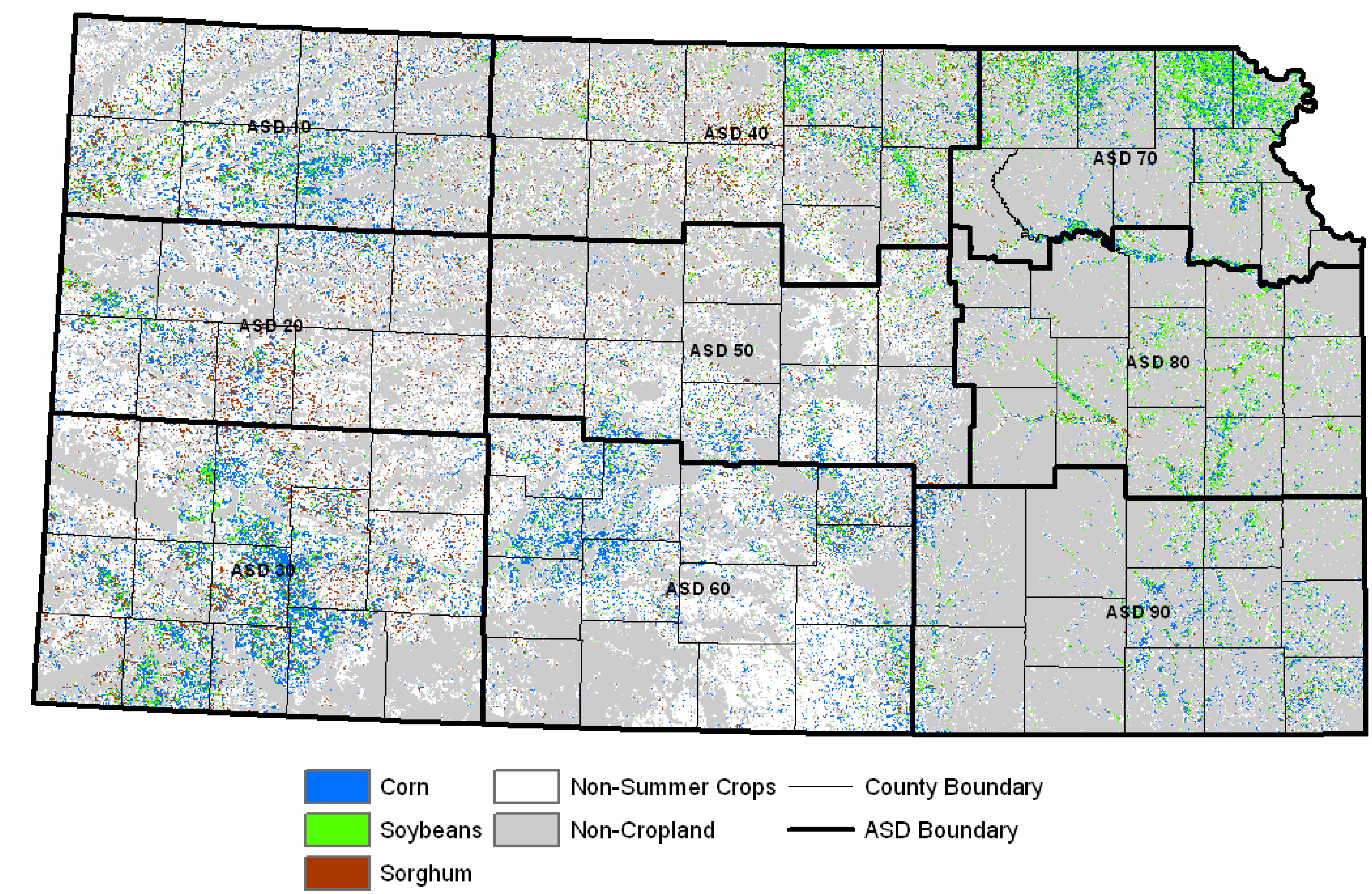

Figure 3.8 2001 summer crops map derived from the 2005 training data and 2001 time-series MODIS NDVI data.

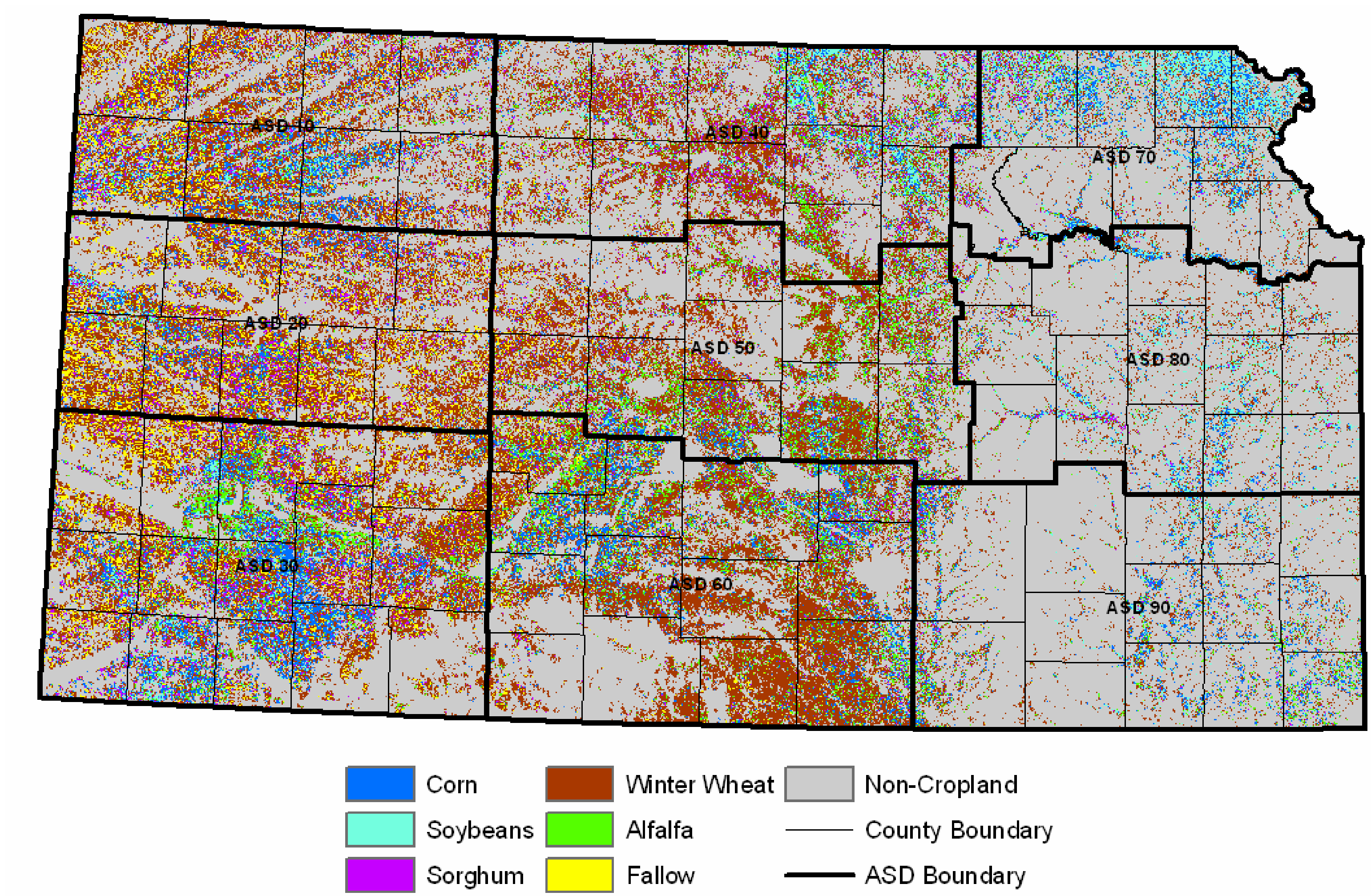

Figure 3.9 2001 map of all crop types derived from the 2005 training data and 2001 time-series MODIS NDVI data.

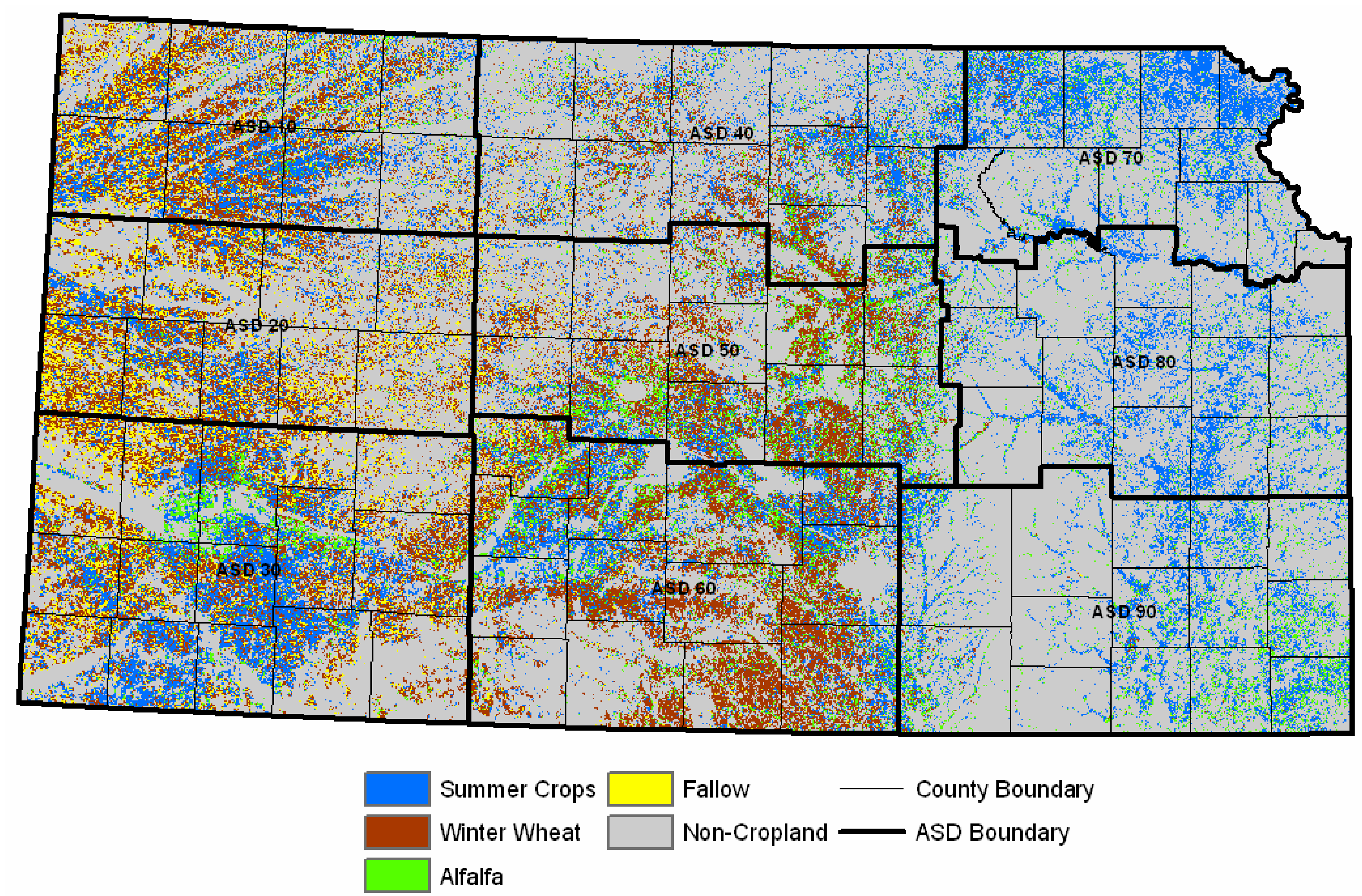

Figure 3.10 2005 general crops map derived from the 2001 training data and 2005 time-series MODIS NDVI data.

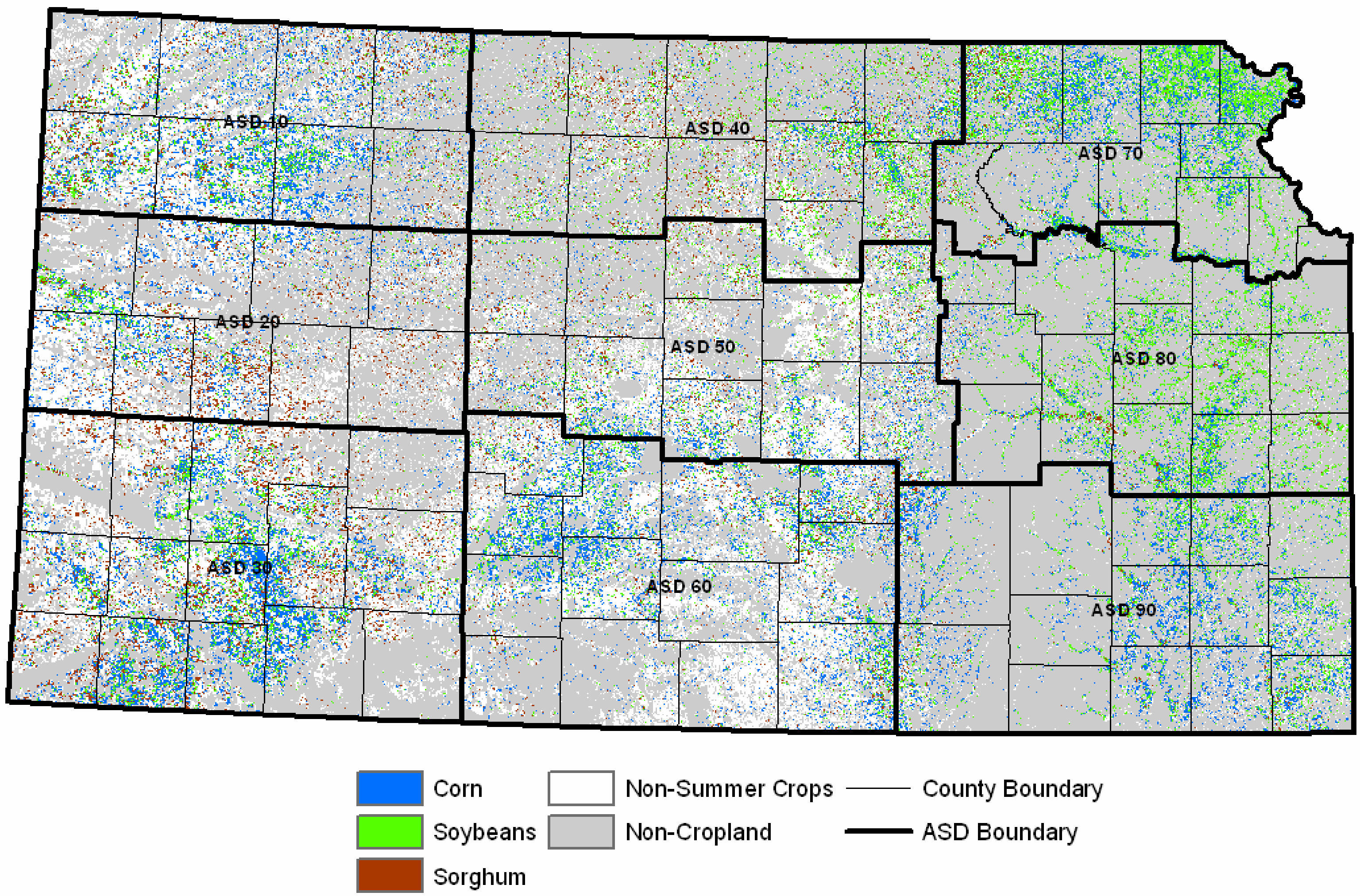

Figure 3.11 2005 summer crop map derived from the 2001 training data and 2005 time-series MODIS NDVI data

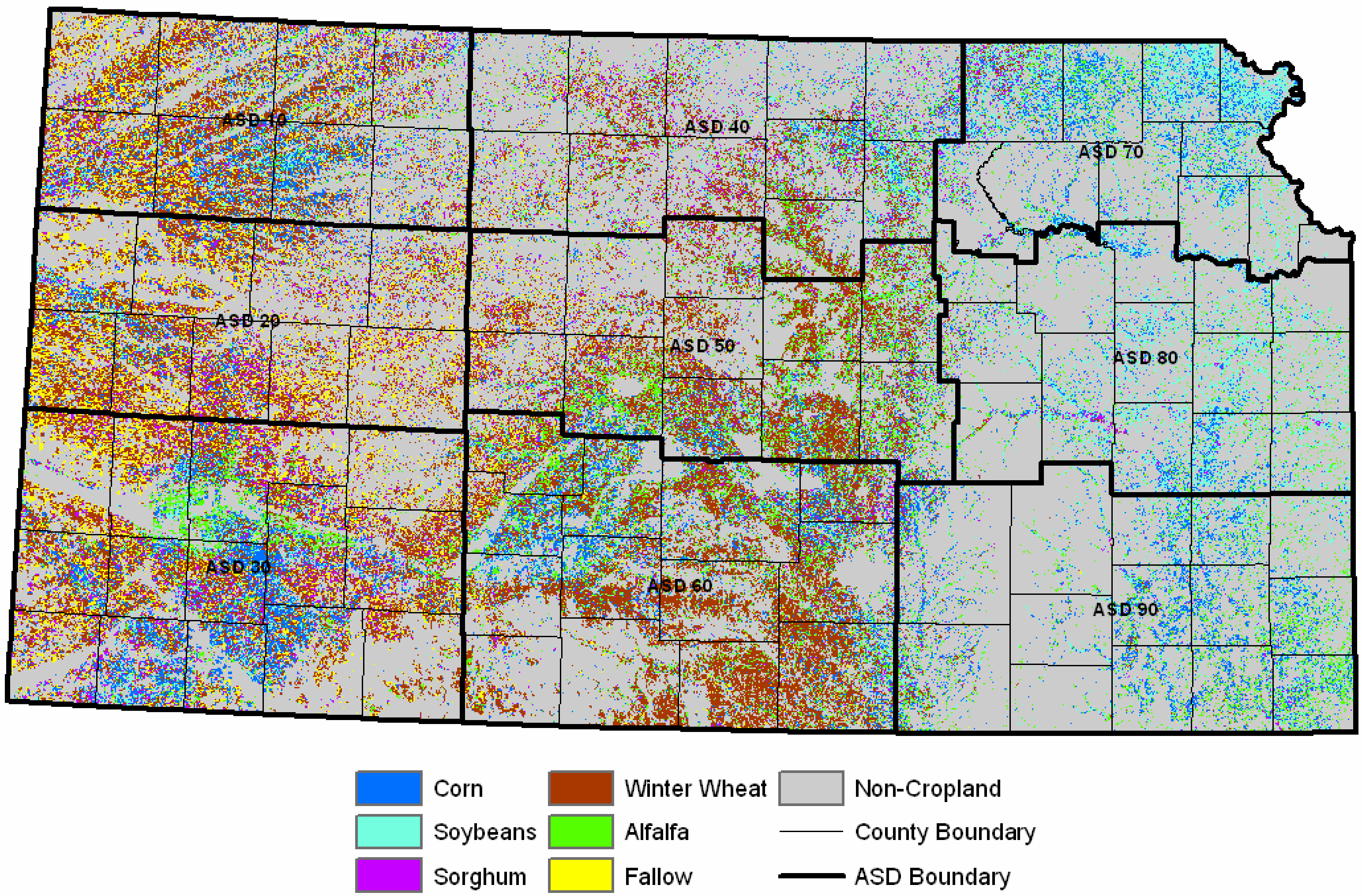

Figure 3.12 2005 map of all crop types derived from the 2001 training data and the 2005 time-series MODIS NDVI data.

Table 3.1 Areal comparisons for 2001 general crops between the MODIS-derived map and USDA reported statistics for Kansas. (2005 field sites as training data)

		MODIS Classification		USDA Area		Difference	
		Acres	% Area	Acres	% Area	Acres	% Area
State	Summer Crops	6,640,308	31.6%	10,300,000	49.0%	-3,659,692	-17.4%
	Winter Wheat	12,553,605	59.8%	9,800,000	46.7%	2,753,605	13.1%
	Alfalfa	1,804,673	8.6%	900,000	4.3%	904,673	4.3%
	Total	20,998,586		21,000,000		-1,414	
ASD 10	Summer Crops	787,114	32.7%	872,000	43.1%	-84,886	-10.4%
	Winter Wheat	1,541,026	64.1%	1,100,000	54.4%	441,026	9.7%
	Alfalfa	76,135	3.2%	49,000	2.4%	27,135	0.7%
	Total	2,404,275		2,021,000		383,275	
ASD 20	Summer Crops	627,737	26.4%	947,000	43.5%	-319,263	-17.1%
	Winter Wheat	1,692,333	71.2%	1,210,000	55.6%	482,333	15.6%
	Alfalfa	56,462	2.4%	18,000	0.8%	38,462	1.5%
	Total	2,376,532		2,175,000		201,532	
ASD 30	Summer Crops	1,381,648	35.9%	1,736,000	49.3%	-354,352	-13.4%
	Winter Wheat	2,141,903	55.6%	1,590,000	45.2%	551,903	10.4%
	Alfalfa	328,168	8.5%	194,000	5.5%	134,168	3.0%
	Total	3,851,719		3,520,000		331,719	
ASD 40	Summer Crops	769,563	30.3%	1,117,000	43.0%	-347,437	-12.8%
	Winter Wheat	1,501,482	59.0%	1,350,000	52.0%	151,482	7.0%
	Alfalfa	272,511	10.7%	129,000	5.0%	143,511	5.7%
	Total	2,543,556		2,596,000		-52,444	
ASD 50	Summer Crops	489,168	18.6%	908,000	35.0%	-418,832	-16.4%
	Winter Wheat	1,735,345	66.1%	1,510,000	58.3%	225,345	7.8%
	Alfalfa	400,664	15.3%	173,000	6.7%	227,664	8.6%
	Total	2,625,177		2,591,000		34,177	
ASD 60	Summer Crops	839,461	21.8%	1,342,000	37.0%	-502,539	-15.1%
	Winter Wheat	2,558,483	66.6%	2,140,000	58.9%	418,483	7.6%
	Alfalfa	445,562	11.6%	149,000	4.1%	296,562	7.5%
	Total	3,843,506		3,631,000		212,506	
ASD 70	Summer Crops	839,461	62.7%	1,244,000	83.4%	-404,539	-20.7%
	Winter Wheat	441,988	33.0%	190,000	12.7%	251,988	20.3%
	Alfalfa	58,387	4.4%	58,000	3.9%	387	0.5%
	Total	1,339,836		1,492,000		-152,164	
ASD 80	Summer Crops	453,065	48.7%	1,032,000	77.2%	-578,935	-28.5%
	Winter Wheat	439,536	47.2%	230,000	17.2%	209,536	30.0%
	Alfalfa	38,120	4.1%	75,000	5.6%	-36,880	-1.5%
	Total	930,721		1,337,000		-406,279	
ASD 90	Summer Crops	453,091	41.8%	1,102,000	67.3%	-648,909	-25.5%
	Winter Wheat	501,509	46.3%	480,000	29.3%	21,509	17.0%
	Alfalfa	128,628	11.9%	55,000	3.4%	73,628	8.5%
	Total	1,083,228		1,637,000		-553,772	

Table 3.2 General crop classification accuracy assessment for 2001 using the FSA field site validation data.

		Reference Data				
		Summer Crops	**Winter Wheat**	**Alfalfa**	**Fallow**	**Total**
Classified Data	**Summer Crops**	**105**	17	3	2	127
	Winter Wheat	76	**149**	2	14	241
	Alfalfa	2	5	**28**	0	35
	Fallow	2	7	0	**26**	35
	Total	185	178	33	42	**438**

Overall Accuracy	70.3%
Producer's Accuracy	
Summer Crops	56.8%
Winter Wheat	83.7%
Alfalfa	84.8%
Fallow	61.9%
User's Accuracy	
Summer Crops	82.7%
Winter Wheat	61.8%
Alfalfa	80.0%
Fallow	74.3%
Kappa	.54

Table 3.3 Areal comparison for 2001 summer crops between the MODIS-derived map and USDA reported statistics for Kansas. (2005 field sites as training data)

		MODIS Classification		USDA Area		Difference	
		Acres	% Area	Acres	% Area	Acres	% Area
State	Corn	2,916,676	43.9%	3,450,000	33.5%	-533,324	10.4%
	Soybeans	2,052,727	30.9%	2,850,000	27.7%	-797,273	3.2%
	Sorghum	1,670,905	25.2%	4,000,000	38.8%	-2,329,095	-13.7%
	Total	6,640,308		10,300,000		-3,659,692	
ASD 10	Corn	395,588	50.3%	588,000	67.4%	-192,412	-17.2%
	Soybeans	203,734	25.9%	60,000	6.9%	143,734	19.0%
	Sorghum	187,792	23.9%	224,000	25.7%	-36,208	-1.8%
	Total	787,114		872,000		-84,886	
ASD 20	Corn	261,580	41.7%	305,000	32.2%	-43,420	9.5%
	Soybeans	127,072	20.2%	24,000	2.5%	103,072	17.7%
	Sorghum	239,085	38.1%	618,000	65.3%	-378,915	-27.2%
	Total	627,737		947,000		-319,263	
ASD 30	Corn	635,754	46.0%	846,000	48.7%	-210,246	-2.7%
	Soybeans	401,191	29.0%	94,000	5.4%	307,191	23.6%
	Sorghum	344,703	24.9%	796,000	45.9%	-451,297	-20.9%
	Total	1,381,648		1,736,000		-354,352	
ASD 40	Corn	238,584	31.0%	219,000	19.6%	19,584	11.4%
	Soybeans	248,737	32.3%	299,000	26.8%	-50,263	5.6%
	Sorghum	282,242	36.7%	599,000	53.6%	-316,758	-17.0%
	Total	769,563		1,117,000		-347,437	
ASD 50	Corn	189,230	38.7%	158,000	17.4%	31,230	21.3%
	Soybeans	147,365	30.1%	207,000	22.8%	-59,635	7.3%
	Sorghum	152,573	31.2%	543,000	59.8%	-390,427	-28.6%
	Total	489,168		908,000		-418,832	
ASD 60	Corn	451,944	53.8%	424,000	31.6%	27,944	22.2%
	Soybeans	262,872	31.3%	273,000	20.3%	-10,128	11.0%
	Sorghum	124,645	14.8%	645,000	48.1%	-520,355	-33.2%
	Total	839,461		1,342,000		-502,539	
ASD 70	Corn	343,767	41.0%	478,000	38.4%	-134,233	2.5%
	Soybeans	366,341	43.6%	613,000	49.3%	-246,659	-5.6%
	Sorghum	129,353	15.4%	153,000	12.3%	-23,647	3.1%
	Total	839,461		1,244,000		-404,539	
ASD 80	Corn	156,278	34.5%	261,000	25.3%	-104,722	9.2%
	Soybeans	173,697	38.3%	633,000	61.3%	-459,303	-23.0%
	Sorghum	123,090	27.2%	138,000	13.4%	-14,910	13.8%
	Total	453,065		1,032,000		-578,935	
ASD 90	Corn	243,951	53.8%	171,000	15.5%	72,951	38.3%
	Soybeans	121,718	26.9%	647,000	58.7%	-525,282	-31.8%
	Sorghum	87,422	19.3%	284,000	25.8%	-196,578	-6.5%
	Total	453,091		1,102,000		-648,909	

Table 3.4 Summer crop classification accuracy assessment for 2001 using the FSA field site validation data.

		Reference Data			
		Corn	**Soybeans**	**Sorghum**	**Total**
Classified Data	**Corn**	**125**	19	22	166
	Soybeans	19	**90**	8	117
	Sorghum	25	9	**61**	95
	Total	169	118	91	**378**

Overall Accuracy	73.0%
Producer's Accuracy	
Corn	73.9%
Soybeans	76.3%
Sorghum	67.0%
User's Accuracy	
Corn	75.3%
Soybeans	76.9%
Sorghum	64.2%
Kappa	.58

Table 3.5 Areal comparison for 2005 general crops between the MODIS-derived map and the USDA reported statistics for Kansas. (2001 field sites as training data)

		MODIS Classification		USDA Area		Difference	
		Acres	% Area	Acres	% Area	Acres	% Area
State	Summer Crops	7,893,146	40.6%	9,300,000	46.2%	-1,406,854	-5.6%
	Winter Wheat	9,139,165	47.0%	10,000,000	49.6%	-860,835	-2.6%
	Alfalfa	2,403,826	12.4%	850,000	4.2%	1,553,826	8.2%
	Total	19,436,137		20,150,000		-713,863	
ASD 10	Summer Crops	904,982	40.0%	780,000	38.0%	124,982	2.0%
	Winter Wheat	1,279,854	56.7%	1,235,000	60.0%	44,854	-3.3%
	Alfalfa	73,616	3.3%	42,000	2.0%	31,616	1.3%
	Total	2,258,452		2,057,000		201,452	
ASD 20	Summer Crops	599,295	32.6%	677,000	34.5%	-77,705	-1.9%
	Winter Wheat	1,213,016	66.1%	1,265,000	64.4%	-51,984	1.7%
	Alfalfa	23,022	1.3%	22,000	1.1%	1,022	0.2%
	Total	1,835,333		1,964,000		-128,667	
ASD 30	Summer Crops	1,446,788	41.6%	1,382,000	43.5%	64,788	-1.9%
	Winter Wheat	1,768,929	50.9%	1,640,000	51.7%	128,929	-0.8%
	Alfalfa	261,699	7.5%	153,000	4.8%	108,699	2.7%
	Total	3,477,416		3,175,000		302,416	
ASD 40	Summer Crops	735,504	42.9%	1,047,000	41.5%	-311,496	1.4%
	Winter Wheat	728,305	42.5%	1,365,000	54.1%	-636,695	-11.6%
	Alfalfa	251,242	14.6%	112,000	4.4%	139,242	10.2%
	Total	1,715,051		2,524,000		-808,949	
ASD 50	Summer Crops	575,020	22.9%	835,000	32.5%	-259,980	-9.6%
	Winter Wheat	1,452,391	58.1%	1,550,000	60.4%	-97,609	-2.3%
	Alfalfa	474,531	19.0%	183,000	7.1%	291,531	11.9%
	Total	2,501,942		2,568,000		-66,058	
ASD 60	Summer Crops	854,256	23.6%	1,134,000	31.9%	-279,744	-8.3%
	Winter Wheat	2,324,685	64.3%	2,270,000	63.9%	54,685	0.4%
	Alfalfa	437,044	12.1%	151,000	4.2%	286,044	7.9%
	Total	3,615,985		3,555,000		60,985	
ASD 70	Summer Crops	1,098,167	78.9%	1,209,000	82.8%	-110,833	-3.9%
	Winter Wheat	91,971	6.6%	195,000	13.4%	-103,029	-6.8%
	Alfalfa	202,310	14.5%	56,000	3.8%	146,310	10.7%
	Total	1,392,448		1,460,000		-67,552	
ASD 80	Summer Crops	877,832	74.6%	1,060,000	82.4%	-182,168	-7.8%
	Winter Wheat	68,527	5.8%	160,000	12.4%	-91,473	-6.6%
	Alfalfa	231,108	19.6%	67,000	5.2%	164,108	14.4%
	Total	1,177,467		1,287,000		-109,533	
ASD 90	Summer Crops	801,302	54.8%	1,176,000	75.4%	-374,698	-20.6%
	Winter Wheat	211,487	14.5%	320,000	20.5%	-108,513	-6.0%
	Alfalfa	449,254	30.7%	64,000	4.1%	385,254	26.6%
	Total	1,462,043		1,560,000		-97,957	

Table 3.6 General crop classification accuracy assessment for 2005 using the CLU validation data.

		Reference Data				
		Summer Crops	**Winter Wheat**	**Alfalfa**	**Fallow**	**Total**
Classified Data	**Summer Crops**	**108**	33	7	12	160
	Winter Wheat	19	**146**	6	10	181
	Alfalfa	4	7	**37**	0	48
	Fallow	3	10	1	**29**	43
	Total	134	196	51	51	**432**

Overall Accuracy	74.1%
Producer's Accuracy	
Summer Crops	80.6%
Winter Wheat	74.5%
Alfalfa	72.5%
Fallow	56.9%
User's Accuracy	
Summer Crops	67.5%
Winter Wheat	80.7%
Alfalfa	77.1%
Fallow	67.4%
Kappa	.61

Table 3.7 Areal comparison for 2005 summer crops between the MODIS-derived map and the USDA reported statistics for Kansas. (2001 field sites as training data)

		MODIS Classification		USDA Area		Difference	
		Acres	% Area	Acres	% Area	Acres	% Area
State	Corn	3,458,110	43.8%	3,650,000	39.2%	-191,890	4.6%
	Soybeans	2,889,223	36.6%	2,900,000	31.2%	-10,777	5.4%
	Sorghum	1,545,813	19.6%	2,750,000	29.6%	-1,204,187	-10.0%
	Total	7,893,146		9,300,000		-1,406,854	
ASD 10	Corn	523,266	57.8%	560,000	71.8%	-36,734	-14.0%
	Soybeans	157,729	17.4%	57,000	7.3%	100,729	10.1%
	Sorghum	223,987	24.8%	163,000	20.9%	60,987	3.9%
	Total	904,982		780,000		124,982	
ASD 20	Corn	283,231	47.3%	320,000	47.3%	-36,769	0.0%
	Soybeans	75,647	12.6%	18,000	2.7%	57,647	10.0%
	Sorghum	240,417	40.1%	339,000	50.1%	-98,583	-10.0%
	Total	599,295		677,000		-77,705	
ASD 30	Corn	748,348	51.7%	800,000	57.9%	-51,652	-6.2%
	Soybeans	293,556	20.3%	100,000	7.2%	193,556	13.1%
	Sorghum	404,884	28.0%	482,000	34.9%	-77,116	-6.9%
	Total	1,446,788		1,382,000		64,788	
ASD 40	Corn	257,769	35.0%	245,000	23.4%	12,769	11.6%
	Soybeans	273,935	37.2%	319,000	30.5%	-45,065	6.8%
	Sorghum	203,800	27.7%	483,000	46.1%	-279,200	-18.4%
	Total	735,504		1,047,000		-311,496	
ASD 50	Corn	285,908	49.7%	135,000	16.2%	150,908	33.6%
	Soybeans	151,716	26.4%	210,000	25.1%	-58,284	1.2%
	Sorghum	137,396	23.9%	490,000	58.7%	-352,604	-34.8%
	Total	575,020		835,000		-259,980	
ASD 60	Corn	522,382	61.2%	390,000	34.4%	132,382	26.8%
	Soybeans	228,655	26.8%	278,000	24.5%	-49,345	2.3%
	Sorghum	103,219	12.1%	466,000	41.1%	-362,781	-29.0%
	Total	854,256		1,134,000		-279,744	
ASD 70	Corn	376,837	34.3%	540,000	44.7%	-163,163	-10.3%
	Soybeans	645,195	58.8%	593,000	49.0%	52,195	9.7%
	Sorghum	76,135	6.9%	76,000	6.3%	135	0.6%
	Total	1,098,167		1,209,000		-110,833	
ASD 80	Corn	185,300	21.1%	310,000	29.2%	-124,700	-8.1%
	Soybeans	617,360	70.3%	673,000	63.5%	-55,640	6.8%
	Sorghum	75,172	8.6%	77,000	7.3%	-1,828	1.3%
	Total	877,832		1,060,000		-182,168	
ASD 90	Corn	275,069	34.3%	350,000	29.8%	-74,931	4.6%
	Soybeans	445,430	55.6%	652,000	55.4%	-206,570	0.1%
	Sorghum	80,803	10.1%	174,000	14.8%	-93,197	-4.7%
	Total	801,302		1,176,000		-374,698	

Table 3.8 Summer crop classification accuracy assessment for 2005 using the CLU validation data.

		Reference Data			
		Corn	Soybeans	Sorghum	Total
Classified Data	**Corn**	**130**	17	19	166
	Soybeans	22	**109**	9	140
	Sorghum	20	8	**48**	76
	Total	172	134	76	**382**

Overall Accuracy	75.1%
Producer's Accuracy	
Corn	75.6%
Soybeans	81.3%
Sorghum	63.2%
User's Accuracy	
Corn	78.3%
Soybeans	77.9%
Sorghum	63.2%
Kappa	.61

Chapter 4

CONCLUSIONS

4.1 RESEARCH OVERVIEW

This study was part of the larger Kansas Next-Generation Land Use/Land Cover Mapping Initiative conducted by the Kansas Applied Remote Sensing Program of the Kansas Biological Survey. The purpose of the land cover map was to update the previous land use database which was 15+ years old. This study had two main objectives. The first was to use 250-meter MODIS NDVI time-series data to discriminate and map the seven major crop classes (corn, soybeans, sorghum, winter wheat, alfalfa, fallow, and double crop) for the state of Kansas and Kansas River Basin for 2005. USDA CLU data were used for training and validation. The second objective was to evaluate the accuracy achieved when using time-series MODIS NDVI response curves for Kansas crops from one year to classify crops for a different year. For the purpose of this study the years 2001 and 2005 were assessed. These years were chosen due to the fact that quality training datasets had already been compiled by Wardlow (2001) and Masialeti (2005).

First Objective

The first objective was to temporally and spatially extend work previously performed in Kansas by Wardlow *et al*. (2007), i.e., to apply the protocol established by Wardlow and extend it temporally to 2005 and to expand this protocol spatially to include the portions of the Kansas River Basin in Nebraska and Colorado. The purpose of this part of the research was to evaluate what level of classification accuracy could be achieved for 2005 using training data from the 2005 USDA Common Land Unit (CLU) dataset. Some specific questions I hoped to answer with this research include: (i) How does this CLU based classification compare to Wardlow's 2001 classification that used training data derived from FSA crop photo data? (ii) Do any regional variations or major misclassifications exist compared to the USDA reported crop acreage and patterns? (iii) What effect does the absence of training and validations data for parts of the study area have on classification accuracies - does this lead to more variation and misclassification?

The results for this objective were promising. The general crop map had a relatively high overall accuracy of 82.4%. The user's and producer's accuracies for specific classes ranged from 86.3% (summer crops) to 66.7% (double crop). The summer crop map had a relatively high overall accuracy of 80.6% (Table 2.6). The user's and producer's accuracies for specific classes ranged from 85.8% (corn) to 72.4% (sorghum).

These results demonstrated that the MODIS-based mapping protocol established by Wardlow is an acceptable option for accurate regional crop mapping in the central U.S. The LULC crop maps produced in this study had a relatively high classification accuracy (82% for the general map and 81% for the summer map). The crop patterns were consistent with the cropping patterns of the region and the reported crop statistics. The diverse range of environmental conditions across the region, however, likely impacted the classification results. Most notable is the east-west precipitation gradient. While measures were taken to attempt to alleviate this impact by making adjustments to the mapping protocol, it likely still influenced the results. The smaller fragmented fields found in the eastern portion of the study area did not appear to cause any significant classification problems at the 250-m resolution. These classification accuracies were consistent with those found in the course-grained west where field sizes are significantly larger. The greatest misclassifications (based on areal assessment) were found to be in Colorado. This is likely due to the lack of training and validation sites for this portion of the study area.

Second Objective

The second objective of the research was to evaluate if training data from 2001 could be used to classify the 2005 data at an acceptable level of accuracy and if training data from 2005 then be used to classify the 2001 data at an acceptable level of accuracy. Some specific questions I hoped to answer with this research include: (i) How do these accuracies vary spatially and by crop type? (ii) How do the cross-year classification accuracies (2005 <>2001) and (2001<>2005) compare to the same-year based classification accuracies (2005<>2005 and 2001<>2001)? (iii) Do the accuracies suggest that this cross-year classification method could be extended spatially and temporally?

The results for this objective were fairly promising. With the 2001 cross year crop classification (using the 2005 training data) the general crop map had a moderate overall accuracy of 70.3%. The class-specific user's and producer's accuracies ranged from 84.8% (alfalfa) to 56.8% (summer crops). The summer crop map had a moderate overall accuracy of 73.0%. The class-specific user's and producer's accuracies ranged from 76.9% (soybeans) to 64.2% (sorghum). With the 2005 cross year crop classification (using the 2001 training data) the general crop map had a moderate overall accuracy of 74.1%. The class-specific accuracies ranged from 80.7% (winter wheat) to 56.9% (fallow). The summer crop map had a moderate overall accuracy of 75.1%. The class-specific accuracies ranged from 81.3% (soybeans) to 63.2% (sorghum).

These results have demonstrated that applying a library of MODIS 250-m NDVI spectral response curves to other years is viable for regional scale crop mapping, yet with lower than desired levels of accuracy. The LULC cross-year crop maps had lower overall classification accuracies (70.3% & 73.0% for the 2001 general & summer maps respectively and 74.1% & 75.1% for the 2005 general & summer maps respectively) when compared to the standard (85%+) for the industry. Yet the general crop patterns were consistent with the known cropping practices in the region. It is likely that the diverse environmental conditions, variation in cropping practices, and plant health between the years had a significant influence on the classification results. These results seem to support Masialeti's conclusion that time series NDVI response curves for crops over a growing period for one year of valid ground reference data may not be useful for mapping crops for a different year without taking into account minor temporal shifts in the NDVI values due to inter-annual climate variations or changes in agricultural management practices.

4.2 FUTURE RESEARCH DIRECTIONS

My study area consisted of the state of Kansas and the areas of the Kansas River Basin that extend into southern Nebraska and Eastern Colorado. The CLU training and validation data were only available for Kansas and Nebraska. No ground reference data were available for the portions of the basin in Colorado. Based on the areal comparisons between the classified map and USDA statistics, the level of agreement was lower in Colorado than in Kansas and Nebraska. This could likely be directly related to the lack of reference data. In the future, it would be interesting to see just how far spatially the study area can be extended beyond the extent of the ground reference data and still achieve an acceptable level of accuracy. It would also be interesting to study the classification accuracy patterns. For instance, perhaps once a certain distance is reached beyond the ground reference data there is a drastic decrease in accuracy or misclassification. Variations in elements such as topography and soil type would also affect the rate of decline in accuracy. Additionally, climatic variations would strongly influence misclassifications. In particular, the study area could be extended to include all of Nebraska, Missouri, Oklahoma, and eastern

Colorado. A classification could be conducted using only ground reference data from Kansas. Then areal comparisons could be conducted at the ASD (or equivalent spatial size) level and see what patterns exist. This would be a good indicator of spatially how far ground reference data can be applied to classify crop types. In addition, in the future this mapping protocol could be extended to include additional crops from the region. For instance, sunflowers are becoming more prevalent.

With Masialeti's research (Masialeti, 2008), his results indicated that there was a high level of agreement between the winter wheat crop profiles for 2001 and 2005 (Figure 4.1). However, Masialeti found that there were differences in the crop profiles for alfalfa and summer crops between 2001 and 2005. He concluded that the differences observed between the alfalfa profiles (Figure 4.2) were mainly due to differences in 'growth and cut' cycles that were not in synchrony. However, the profiles of summer crops – corn (Figure 4.3), soybeans (Figure 4.4), and sorghum (Figure 4.5) – displayed a shift to the right (i.e. later in the growing season) by at least one composite date, indicative of the late crop emergence and a delayed growth and senescence cycle in 2005 compared to 2001. Masialeti's results, particularly for alfalfa and summer crops, seem to suggest that valid ground reference data from one year may not be useful for mapping crops for a different year without taking into account minor temporal shifts in the NDVI values due to inter-annual climate variations. Regarding the future directions of this research two things must be considered; first Masialeti's findings and second, the relatively low level of accuracy that resulted from the cross-year classifications conducted during this research. Note that the classification accuracies for alfalfa and summer crops (sorghum in particular) were especially low. Based on the formal assessment, overall accuracies for alfalfa ranged from 72.5-84.8%. The range of values for corn (73.9-78.3%) and soybeans (76.3-81.3%) were also relatively low. Overall accuracies for sorghum were even lower, ranging from 63.2-67.0%. In the future, some steps could be taken to improve the overall classification accuracies. Starting with the 2001 ground reference data, it would be interesting to temporally shift the NDVI values for certain crop types. For instance, the NDVI values for the ground reference data for 2001 summer crops could be shifted one period to the right. Then the NDVI values for the alfalfa ground reference data could be temporally shifted to match the 'growth and cut' cycles associated with those found in 2005. Once these changes have been applied a new cross-year classification could be conducted. More than likely, this would significantly improve the classification accuracy. Similarly, with the 2005 ground reference data, the NDVI values for summer crops could be temporally shifted one composite period to the left and the NDVI values for alfalfa could be shifted to match up with the 'growth and cut' cycles in 2001. Again a new classification could then be conducted and likely a higher level of accuracy could be achieved.

4.3 REFRENCES

Masialeti, Iwake, 2008. Assessment of Time-Series MODIS Data for Cropland Mapping in the U.S. Central Great Plains. PhD dissertation, University of Kansas.

Wardlow, Brian D., Egbert, Stephen L., Kastens, Jude H., 2007. Analysis of time-series MODIS 250 m vegetation index data for crop classification in the U.S. Central Great Plains. *Remote Sensing of Environment* 108, 290–310.

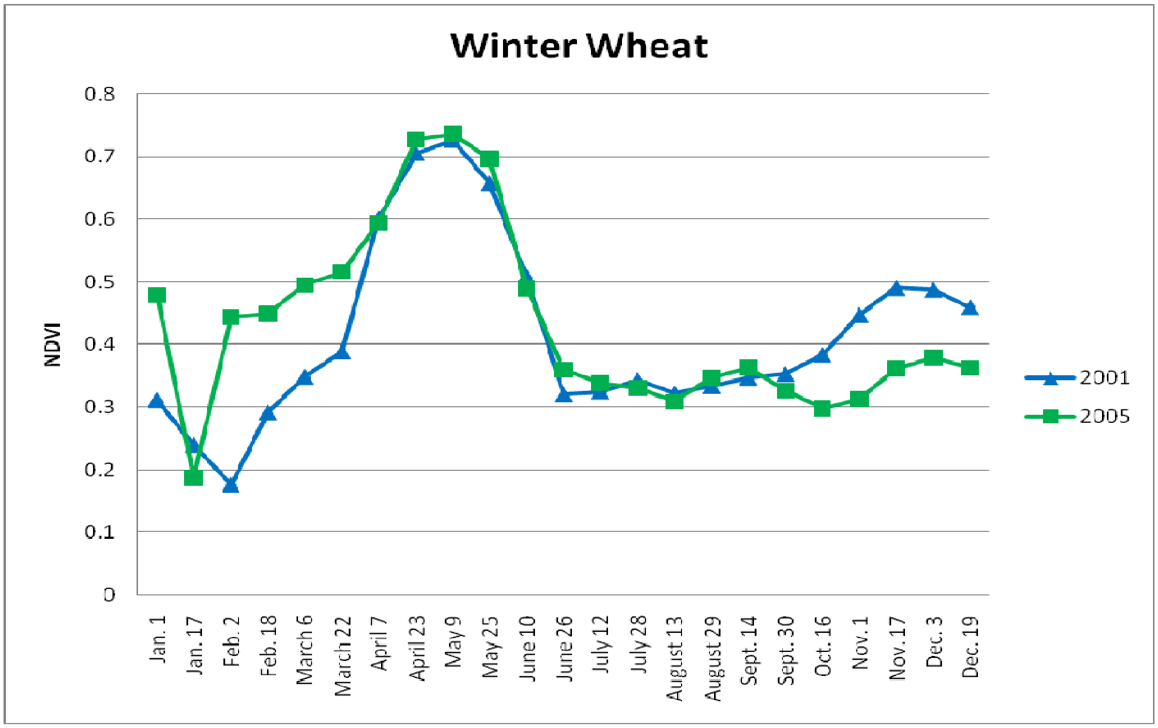

Figure 4.1 2001 and 2005 comparison of NDVI curves for Winter wheat

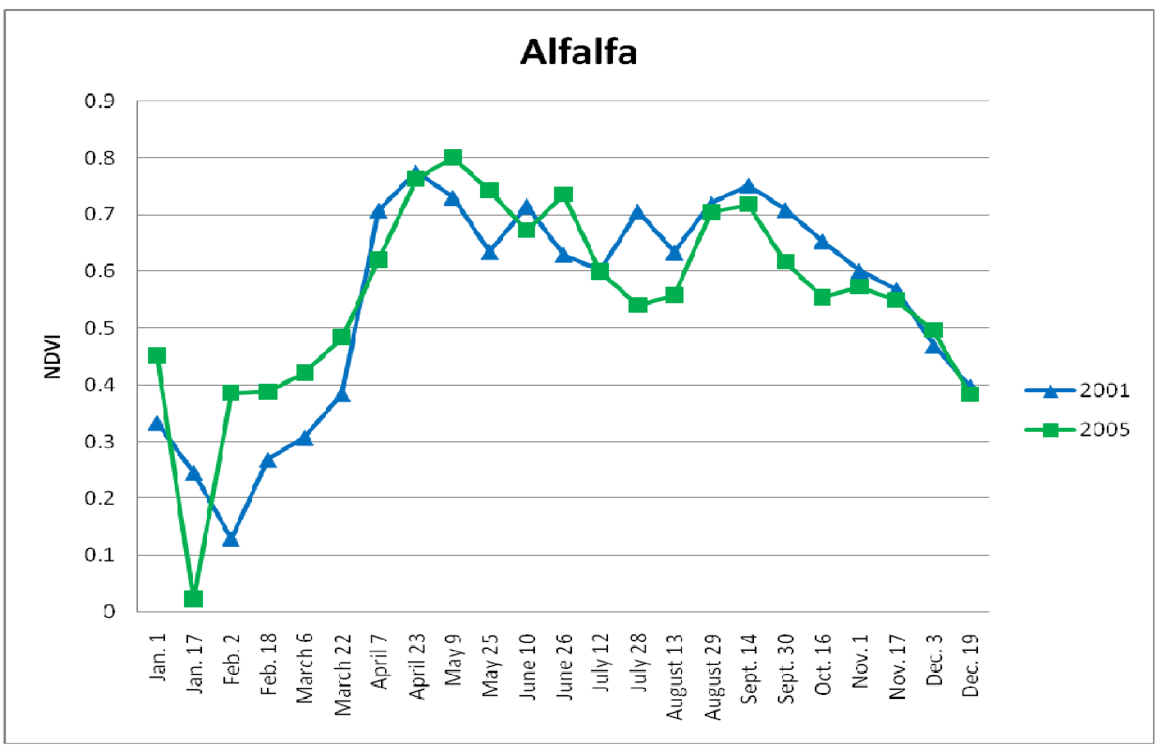

Figure 4.2 2001 and 2005 comparison of NDVI curves for alfalfa

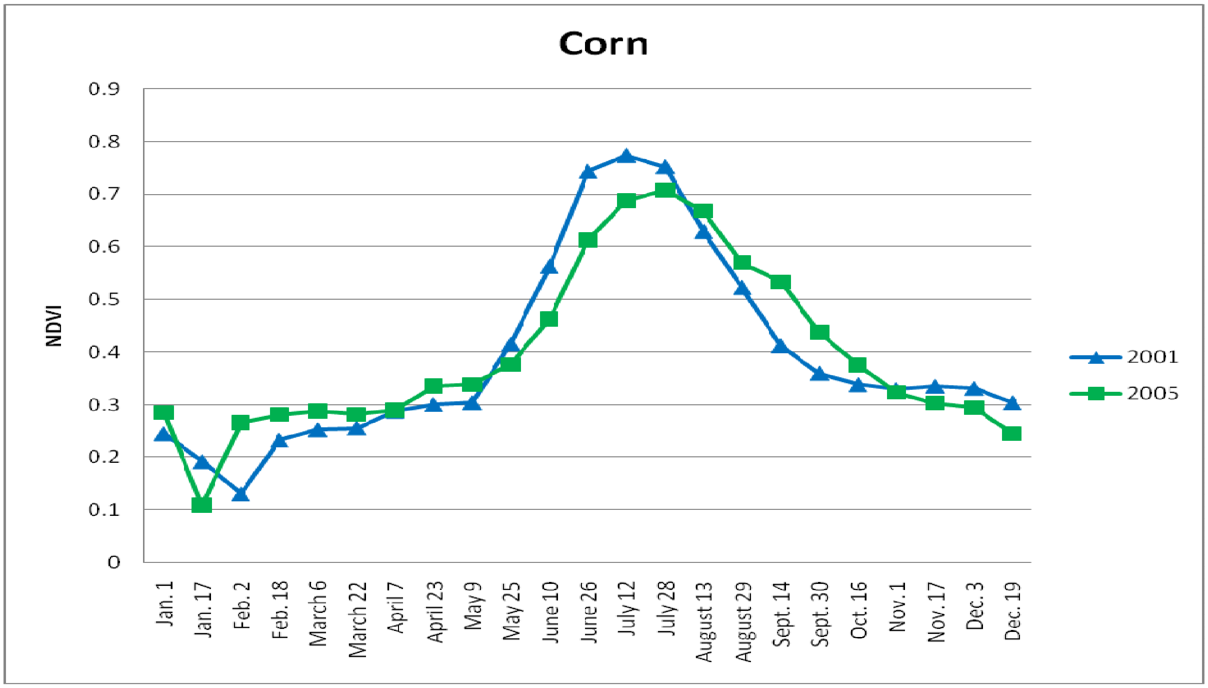

Figure 4.3 2001 and 2005 comparison of NDVI curves for corn

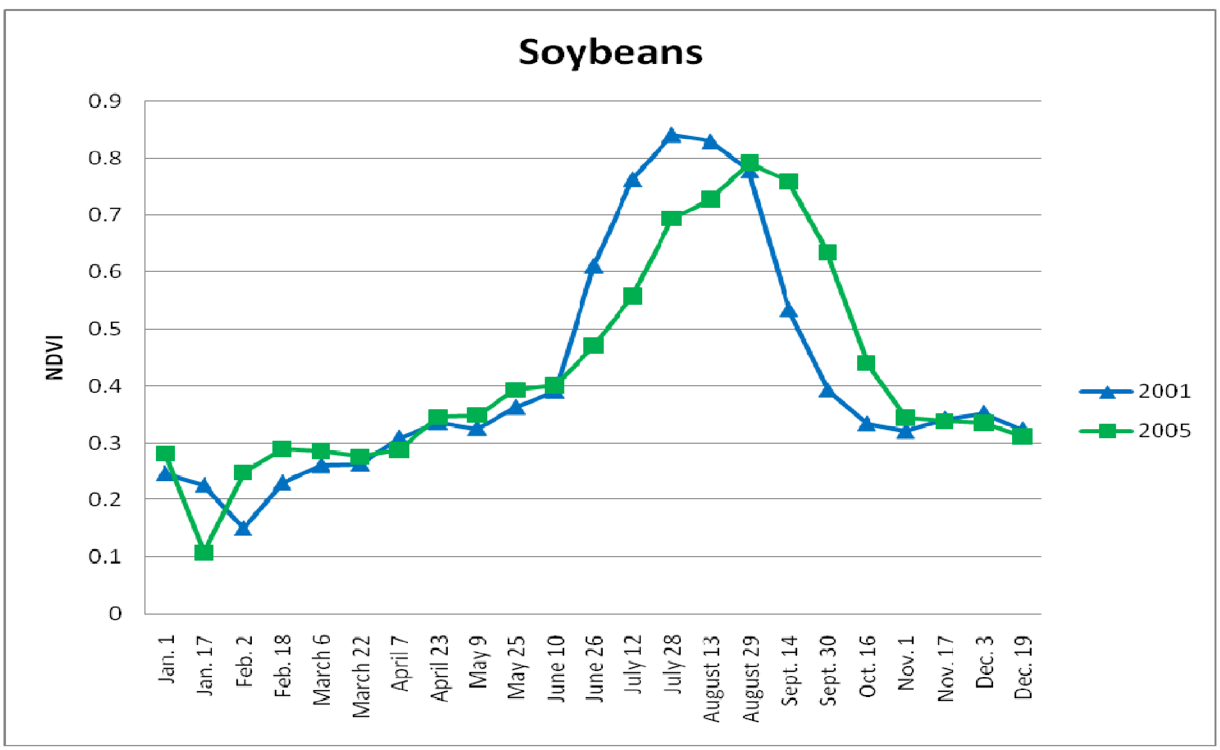

Figure 4.4 2001 and 2005 comparison of NDVI curves for soybeans

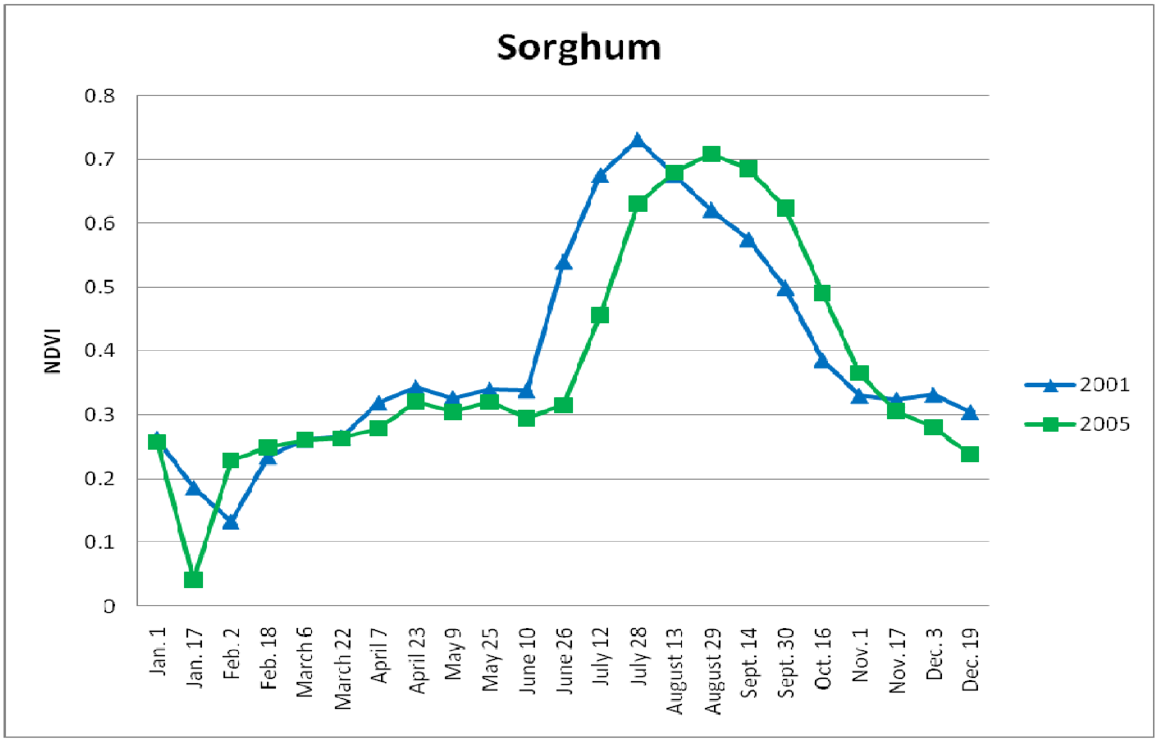

Figure 4.5 2001 and 2005 comparison of NDVI curves for sorghum